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Investigating the Direct Application of Chaos Theory to Detect, Analyse and Anticipate High-Level Variability in the Logistics Demand of Third Party Logistics

Chrisoula Papadopoulou

Department of Business and Management
University of Glasgow

Presented as a thesis for the degree of Ph.D.,
in the University of Glasgow.

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To my mum,

"Σε ευχαριστώ για όλα μαμά.
Χωρίς εσένα τίποτα από όλα αυτά δεν θα ήταν εφικτό!"

Abstract

Third party logistics providers operate in an environment where the customer demand shows high-levels of variability. Existing methods of analysis and prediction cannot capture these types of fluctuation. Newer methods of analysis, and the identification of potential chaotic conditions to explain these intense oscillations, have not been tested for applicability in these situations. The purpose of this thesis is to investigate whether the direct application of chaos theory can efficiently detect, analyse and anticipate high-level variability in the logistics demand of third party logistics (TPL).

The research involves a single case study analysis. The variable investigated is the logistics demand extracted from the EDI files of the company in a time-series format. The time scale of the data is over two years. A framework of data analysis, called CASTS (Chaotic Analysis of Short Time Series), is constructed in order to analyse the data. It is an amalgamation of linear, non-linear and chaos theory based techniques selected to allow the detection, analysis and possible anticipation of the underlying data set. The CASTS method is composed of the application of the autocorrelation function, power spectrum, BDS statistics, mutual information, phase space plots, correlation dimension, Lyapunov exponent and finally, Hurst exponent tests. In addition a surrogate data test is performed in order to achieve a 95% level of confidence in the results.

The importance of this research is fourfold. First, it proposes a solution for third party logistics to improve their operational efficiency through an

enhancement in their forecasting, planning and control abilities. Secondly, it adds new knowledge to logistics management in two ways; it brings together two different sciences and provides insights that have not been explored before and; it succeeds to identify, for the first time, the presence of chaotic behaviour in real logistics data and thus give a new direction to logistics research. Thirdly, it provides CASTS as a new framework of analysis for the detection of chaotic behaviour in short time series that was not previously applied in social sciences. Finally, it has tremendous implications for industry; it concerns the logistics anticipation, planning and control. It assists companies to focus their efforts in understanding the structure and restraining the behaviour of their demand patterns rather than focusing in reactive actions.

In addition, chaos was found to be a "*potential behaviour*" of high-variability in logistics demand. The direct application of chaos theory can efficiently identify, analyse and anticipate high-variability in logistics demand. However, special attention should be placed on the limitations of the suggested methodology and any generalisation of the results should be made cautiously. Further improvement of the method of CASTS is also discussed in the thesis.

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Chrisoula Papadopoulou

Preface

During most of the period of research presented in this thesis, the author was in receipt of a PhD studentship awarded by the Centre for Supply Chain Management, which is partially funded by the Charted Institute of Purchasing and Supply. The author was under the supervision of Prof. Douglas Macbeth at the Department of Business and Management of the University of Glasgow.

The work presented in this thesis is directed towards the detection, analysis and prediction of chaotic patterns in empirical logistics data series.

There are five main parts comprising this thesis; overview, literature review, methodology, findings, discussion and conclusions. Part 1 consists only of Chapter 1, which serves as an overview of the thesis. The chapter is composed of four sections. Section 1.1 sets the background of the research. It starts with a general, brief description of the two main fields examined in this study, third party logistics and chaos theory, and gradually narrows down to the research problem of the study. Section 1.2 and Section 1.3 state the research problem and its ensuing research questions. Section 1.4 justifies the importance of the research. Section 1.5 briefly introduces the research methodology and Section 1.6 discusses the limitations and key assumptions of the research. Section 1.7 points to the Glossary, found at the end of the thesis, for a complete list of definitions of the main concepts used in this thesis. Finally, Section 1.8 presents the organisation of the thesis and Section 1.9 summarises the key issues of the chapter.

Part 2, the literature review, aims at building the theoretical foundation upon which the research is based. It consists of three chapters. Chapter 2 provides the necessary theoretical background of third party logistics and defines the importance of investigating the issue of high variability in the logistics demand of third party logistics. Section 2.1 introduces the field of third party logistics. Section 2.2 provides a general overview of the third party logistics industry, by defining TPL and its role in logistics chains, the main steps of the TPL historical development, and finally classifying the main current research directions in TPL research. Section 2.3 identifies and describes the main elements and functions of TPL operations. Section 2.4 identifies and describes the main current challenges in the third party logistics industry. Finally, Section 2.5 summarises the main points of this chapter and concludes by stressing the importance of prioritising the investigation to identify the main sources causing high variability in logistics demand.

Chapter 3 continues the analysis of the previous chapter by focusing on the issue of high variability in logistic demand. Section 3.1 provides a general overview of data variability. Section 3.2 defines and describes the main characteristics of demand variability. It is also summarises the main research directions in high-level variability. Section 3.3 identifies the main sources of high-level variability in logistics. Section 3.4 discusses the issue of logistics variability in third party logistics demand and Section 3.5 identifies the impact of high-variability on TPL operations. Section 3.6 presents the current approaches used to manage high-level variability in logistics demand. Finally, Section 3.7 summarises the key points of this chapter. This chapter gives a comprehensive list of all factors causing high variability in logistics demand.

The last chapter of Part 2 is Chapter 4, which introduces the theory of chaos. Section 4.1 provides a general overview of chaos theory. Section 4.2 gives a brief summary of the historical development of chaos theory in both the natural and the social sciences. Section 4.3 defines scientific chaos, while Section 4.4 introduces the main elements of chaos – aperiodicity, deterministic system, bounded behaviour, sensitivity to initial conditions and phase space. Section 4.5 describes the main causes of chaos starting from the mathematical approach that chaos is the result of certain irregularities developed in the system as a result of sensitivity to initial conditions. Then, the discussion switches towards a more theoretical approach looking at feedback and self-organisation as potential factors encouraging irregularities to appear and continue in a system. It also discusses the measure of entropy and the issue of randomness Section 4.6 reviews the issues arising from the investigation of chaos and Section 4.7 outlines current direct applications of chaos theory in management. Finally, the chapter concludes with Section 4.8 summarising the key points of the chapter.

Part 3 is devoted to the research methodology applied in this study aiming at describing the data collection and data analysis methods. It is divided into two chapters. Chapter 5 describes the research design, data collection and the selection criteria for the chosen data analysis. Section 5.1 relates Part 2 with Part 3 in order to explain the data collection methods and procedures. Section 5.2 describes the research process, while Section 5.3 the research design that the author has created for this research. Section 5.4 justifies the selected research method and Section 5.5 proceeds in describing the data collection methods used in this research. Section 5.6 explains the steps taken in order to prepare the raw data for the data analysis phase. Finally, Section 5.7 summarises the main points of the chapter.

The last chapter of this part, Chapter 6 presents the method of CASTS as a new framework for data analysis and explains in depth all the relevant tests and techniques. Section 6.1 explains the relevance of data collection and the necessary preparation of the data before proceeding to the data analysis. Section

6.2 clarifies the philosophy of the data analysis. Sections 6.3 to 6.6 thoroughly describe all the tests used to analyse the data. Concisely, the proposed methodology of data analysis consists of three main phases; description of the data, search for correlations and identification of the characteristics of the underlying system. Additional to the tests included in the above three phases, CASTS proposes two surrogate data tests performed at the end of Phase II and Phase III. Although these two tests are not directly related to the data analysis, they are necessary to increase the validity of the results. Section 6.8 describes the issues of validity, reliability and pitfalls in data analysis. Finally, Section 6.9 summarises the main points of the chapter.

Part 4 is divided into two chapters and involves the presentation of the data analysis results. Chapter 7 displays the results of the analysis of the raw data of EXEL Logistics/FORD, while Chapter 8 exhibits some additional results from further analysis of the data. Both chapters follow the same structure with the data analysis phases presented as in the previous chapter.

Part 5 is composed of Chapter 9. The purpose of Chapter 9 is to discuss the findings generated from the empirical analysis, to compare the results and assess the relevant associations. Section 9.1 explains the purpose and the importance of this chapter. Section 9.2 to Section 9.4 compares the results of the data analysis of the two previous chapters and outlines the main observations coming from the above comparison. Section 9.5 summarises the main points of this chapter.

Finally, Part 6 is composed of Chapter 10, the purpose of which is to summarise the main conclusions drawn about each research question and research problem. Section 10.1 links all the chapters together as an introduction to the following discussion. First, Section 10.2 summarises the conclusions about the research questions of the thesis, while Section 10.3 summarises the conclusions about the research problem. Section 10.4 and Section 10.5 present the implications for theory and practice respectively. The limitations generalisability issues generated during the execution of this research are discussed in Section 10.6 and Section 10.7 respectively. Finally, Section 10.8 explains the main implications of the study on further research and finally, in the last section, Section 10.6, summarises the main issues and conclusion drawn from this research.

Finally Appendix 1 presents the case study background. Appendix 2 describes the C and Matlab code applied to aggregate the data of the first case study, and appendices 3 to 8 illustrate complementary results of the data analysis. The thesis also includes a glossary of the main concepts used during this research.

PART I

OVERVIEW

Chapter 1:

INTRODUCTION

Chapter 1

Introduction

Chapter 1:

Introduction

1.1 Background to Research

Heading towards the new millennium, the intensifying pace of change and its ensuing complexity had puzzled many analysts (Toffler, 1984). Economic, regulatory, technological (Sheffi, 1990) and cost efficiency pressures (Virum, 1993) increased the number of companies outsourcing and subcontracting their logistics function (Berglund, 2000), encouraging in that way the rapid growth of third party logistics (TPL). Estimates anticipate that more than 50% of logistics functions will be outsourced by the 21st century (Witt, 1995).

As TPL industry heads towards its maturity stage, the increasing need for outsourcing of the logistics function made suppliers become more conscious about their TPL provider selection and the TPL providers to become more aware about the escalating necessity of maintaining high efficiency in their operations. Sink and Langley (1997) came up with a managerial framework for the acquisition of such TPL services, especially when many TPL providers fail to satisfy their promise and many alliances fail to reach the desired efficiencies (Brown and Pattinson, 1995). It is a fact that up to two thirds of all relationships fail before the member firms intended the relationship to end (Brown & Pattinson, 1995; Cravens, Piercy, & Shipp, 1995; and Sherman & Stanford, 1992), and up to 70% of all relationships fail to produce the outcomes anticipated by their organisers (Brown & Pattinson, 1995). Therefore, the pressure for operational efficiency becomes of paramount concern, and at the same time a competitive opportunity, in third party logistics industry.

One way to improve operational efficiency is to improve forecasting. As Pettigrew states, "changes have multiple causes and are to be observed by loops rather than by lines" (Pettigrew, 1990). In the same way, operational inefficiency is the result of many factors interrelated and affecting each other. According to the logistics loop proposed by Lawrence, forecast drives the effectiveness of most of the operational logistics functions (Lawrence, 1999: 44). Therefore, any fluctuation in the logistics demand will have an effect on the operational efficiency. Evidence has shown that one of the main current challenges in TPL industry is the issue of high-level variability (Cowper, 1998; Buck, 1990). As a result of the above interrelation, the identification of the behaviour of the logistics demand becomes difficult to be identified and analysed (Lummus & Vokura, 1999).

One of the main difficulties with this type of fluctuation is that current forecasting techniques are limited to the type of data that they can efficiently identify, analyse and predict (Klassen & Rohlede, 2001); more complex types of behaviour will normally be classified as random. Thus, not all types of high-level variability in logistics demand can be effectively analysed and anticipated with the available forecasting tools, and as a result, the need emerges for a more advanced method of analysis that can detect, analyse and anticipate the more complex types of behaviour.

Chaos theory seems to be a good candidate to explore this issue. The direct application of the theory can provide the necessary mathematical tools to help identify, analyse and/or anticipate high-level variability in logistics demand. It can provide valuable information about the structure and behaviour of the underlying system. In social sciences and management the direct application of chaos theory is still in its embryonic stage. However, examples of applications can be found in the field of finance to explore the high-level fluctuations in the stock exchange (Connelly, 1996; vonRönik, 1996), in political science to investigate patterns of conflict between Asia and the USA (Thietard & Forgues, 1997) and in logistics to investigate the selection patterns of warehousing (Wilding, 1997). The common interest of all the above examples is to investigate a new approach of identifying, analysing and predicting future patterns of highly fluctuating systems that cannot be captured by the traditional methods. Therefore, there is clearly a need to further explore the direct applicability of chaos theory to detect, analyse, and predict high-level variability in the logistics demand of third party logistics in order to improve their operational efficiency.

1.2 The Research Problem

Based on the above discussion, the research problem of this thesis can be stated as follows:

> *Third party logistics providers operate in an environment where there customers' demands show high levels of fluctuation. Existing methods of analysis and prediction cannot capture these types of fluctuation. Newer methods of analysis and the identification of chaotic conditions have not been tested for applicability to these situations.*

Essentially it is argued that the direct application of chaos theory can be used effectively to detect, analyse and anticipate high-level fluctuations in the logistics demand of third party logistics. Consequently, it is suggested that the enhancement in the anticipation of future patterns would improve the TPL operational efficiency.

This thesis explores the above research problem in two different levels. First, based on an extensive literature review, the main sources creating high-level variability in the logistics demand and their impact on the TPL operations are investigated. Then, a new methodological framework, called CASTS, is constructed in order to test the direct applicability of chaos theory, and investigate signs of chaotic behaviour on an empirical data set.

1.3 The Research Questions

The four research questions generated, in order to answer the research problem, are discussed throughout the thesis, with details found in Chapter 3, Chapter 6, Chapter 7 and Chapter 8 respectively. Additional discussion on these questions can also be found in Chapter 9 and Chapter 10. Briefly, the research questions can be stated as follows:

- *What are the sources of high-level variability in logistics demand?*
- *How are third party logistics operations affected by high-level variability in logistics demand?*
- *Are there any signs of chaotic behaviour in logistics demand?*
- *How can empirically obtained short-time series data be used to test the direct applicability of chaos theory analysis in detecting, analysing, and predicting patterns of high - level variability logistics demand data?*

1.4 Justification for the Study

This thesis can be justified on the grounds of the (a) importance of the research in the third party logistics industry, (b) specification of the research questions, (c) new methodological approach, and (d) potential applications of the findings.

1.4.1 Importance of Research in TPL Industry

This research is important to TPL industry because of the increasing pressures for logistics efficiency in TPL operations. As various industries have shifted towards the utilisation of third party logistics providers, competition in TPL industry has grown stronger. Companies are seeking to outsource their logistics function with TPL providers that they can achieve the desired efficiencies required for them to operate (Brown & Pattinson, 1995). The third party logistics provider has to: be an effective means of cost containment, reduce internal capital requirements, and provide strategic logistics advantages through a superior customer service. Third party logistics can achieve this by focusing on improving their operational, managerial and strategic efficiency (Berglund, 1997). Current research indicates that from these factors the operational efficiency is the most important but also the most difficult to be achieved (Chapter 2), as a result of high uncertainty in logistics demand (Chapter 3). Thus, the need to improve the efficiency of TPL operations by focusing on the improvement of logistics demand anticipation becomes vital.

1.4.2 Specification of the Research Questions

The second justification of this research is related to the negligence of previous researches to direct the investigation towards chaos analysis. More specifically, current research directions in managing high-level variability in logistics demand can be divided into two broad classifications; the managerial, and the operational approach. The managerial approach can be further divided into three more research directions; demand management (Vollmann, Berry & Whybark, 1992), information integration (Lee, Padmanabhan & Whang, 1997) and the demand or "pull" approach (Christopher, 1997). The operational approach can be further classified into two categories; forecasting enhancement (Tzefetas & Kapsiotis, 1994), and forecasting integration (Mentzer & Schroeter, 1994). Forecasting enhancement focuses on improving multi-variable prediction techniques. Forecasting integration suggests either an amalgamation of several anticipation methods or a combined forecasting and managerial approach.

A review of the above approaches suggests that the managerial approaches are always reactive to demand variability, while the operational approaches focus on improving already used methods rather than investigating new approaches that could turn out to be better than those already in use. Thus, the direct application of chaos theory to detect, analyse and anticipate logistics demand with high variability could open new avenues towards a new theoretical conceptualisation. Popper adds that, "in most cases we have, before falsifying a hypothesis, another one up our sleeves; for the falsifying experiment is usually a crucial experiment designed to decide between the two" (Popper, 1959: 87).

1.4.3 New Methodological Approaches

The third justification of this thesis is related to the current methodological frameworks used to investigate first the demand variability and to the direct application of chaos theory to social sciences and management.

Traditional analysis of demand behaviour have relied heavily on subjective, univariate and multivariate forecasting techniques such as the Delphi technique, exponential smoothing, or Box-Jenkins (Lambert & Stock, 1993: 562-563, Chatfield, 1996: 66-90). The efficiency of these techniques reduces as the trend, seasonal, or random variation increases. In addition, those methods cannot capture hidden or slow changes in the system (data). Finally, because they focus exclusively on prediction, they provide no information about the structure of the system; their analysis is limited purely to time related information.

As mentioned in Section 1.1, the direct application of chaos theory to management is in a primitive stage. However, current attempts lack first, the depth of a "holistic" or a complete methodological framework to investigate chaotic behaviour (Chapter 2 & Chapter 3) and second, the applicability of such an approach to fit the needs of business data[1].

For that reason, most of the current researches use simulated, instead of empirical (or real data). The methodologies used in simulation are mainly either stochastic (Davis, 1993) and/or deterministic in nature (Wilding, 1997). There are two main weaknesses in using simulation modelling. First, the model is subject to human interpretation. And second, even if the model used is reliable, many times the analysis is based on traditional statistical methods, instead of more advanced non-linear methods, such as chaotic analysis, that can analyse fractal non-linearities. This study uses chaotic analysis to detect, analyse and anticipate intensely fluctuating behaviour in real logistics demand in short-time series.

It should be noted that no work known to the author has investigated logistics demand fluctuations using chaotic analysis either by using simulated or real data. In addition, most of the current attempts to investigate and apply chaotic analysis are focused on detailed investigation of specific tests rather than using a holistic framework to analyse the data.

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[1] There are two characteristics of business data; it is short and it has high levels of noise. Short data is defined as any time series data that has less than 600 data points. Noise is created by random events such as a lorry breakdown.

1.4.4 Potential Application of Findings

The usefulness of the potential applications of this research's findings can be classified into three categories; improve anticipation, logistics planning and logistics control.

Improve Anticipation

The direct application of chaos theory has potential at two levels. First, it could provide a new analytical tool to give novel insights into the systems' behaviour that could not be captured by traditional methods. For instance, it can pick up slow or hidden changes, identify cycles of behaviour, and define moments when the system shifts from one style of behaviour to another – currently perceived as random incidents. That would allow management to make better decisions and be able to keep the system under control avoiding "unintentional disruptions to the limit cycles" (Priesmeyer & Baik, 1989). Better understanding of the behaviour of the system could allow management to stabilise the system in the long run.

Finally, the second reason is that chaos theory identifies signs of chaotic behaviour in the system. This avoids the mistake of using linear methods to forecast and therefore to make wrong decisions. Even better, if the system proves to be random a stochastic approach might be better. That would prevent management making wrong decisions that could prove to be inappropriate.

Improve Logistics Planning

Logistics planning could benefit as a result of better anticipation of the logistics demand. The awareness of the frequency and the manner of logistics demand changes can provide deeper understanding of a system's structures, volatilities, and abilities (Choraphas, 1994). The structure can indicate the transmission of rules and information to the system. In addition, it can provide a better picture of its dynamic nature. Therefore, non-linearity or volatility produces regularities and irregularities that can lead a system to unpredictable or chaotic behaviour. Nevertheless, the existence of chaos in complex and dynamic systems makes them spontaneous and adaptive. In unending evolution and chaotic behaviour "the new ideas and innovative issues are challenging the status quo, seeing to it that the entrenched old guard will eventually be overthrown – whether it consists of people or rules" (Choraphas, 1994).

Improve Logistics Control

The direct application of chaos theory can encourage better TPL control. "Events are unique and small... consequences for a particular company depend upon how that company and its competitors act, such consequences are unpredictable" (Stacey, 1991). Therefore factual prediction becomes an issue, especially in long-term forecasting. The reason is that "in practice, one can only fix their [systems'] initial conditions with finite accuracy, and errors can increase exponentially fast" (Schuster, 1984). Likewise, feedback mechanisms feed information back to the system causing chaotic patterns of behaviour. Current mathematical and computing abilities cannot support this kind of multi-variable long-term analysis. At this point, chaos theory proposes control instead of long-term prediction. According to Ditto, Spano and Linder (1995), as long as small incidents are those responsible for big effects, they can be easily and inexpensively monitored.

1.5 Methodology

The decision of the above methodology is based on an extensive literature review on the methods for detection of chaotic behaviour in short-time series data, and it is based on non-linear statistical analysis on real short-time series data. The purpose of the analysis is to explore the behaviour and structure of demand fluctuations. It is divided into three main phases (1) data description (2) correlation search, and (3) characteristics of the underlying system. The first phase provides descriptive information about the time series being analysed. The actual analysis starts with the second phase - the search for correlations - that is, testing the series for independence and looking for possible correlations. The next phase investigates the criteria for chaos. It looks at the phase space state, correlation dimension, largest Lyapunov exponent, and Hurst exponent. Additional to the tests consisting these three phases, two surrogate data tests are also included. Both surrogate data tests try to validate that the results of the above analysis are neither random nor the product of temporal linear behaviour (more details can be found in Chapter 6). The software packages used for the above analysis are: *TISEAN* (Kanzt & Schreiber, 1996), *Chaos Data Analyser (CDA)* (Sprott & Rowlands, 1995) and *SPSS* (SPSS Inc., 1997). TISEAN is used to perform the mutual information and the creation of the surrogate data sets.. The CDA is used to perform the BDS statistics test, correlation dimension, largest Lyaponov exponent and Hurst exponent tests and to construct the phase space plots. The SPSS was used to perform the autocorrelation. It should be mentioned that CASTS is structured in such a way as to identify all types of behaviour; linear, non-linear and random. However, maximum benefit comes from detecting and analysing the chaotic behaviour.

There are some important points that should be mentioned about CASTS. The direct application of chaos theory is restricted by the nature and size of data. Very short-time series data cannot be quantitatively analysed with methods based on chaos theory. Nevertheless, the direct application of chaos theory advances the traditional approaches on the grounds of case sensitivity, "learning" and advanced prediction. Chaotic analysis generates individual results depending on the characteristics of the systems being analysed. In addition, the more data that is fed into the analysis the more accurate the results will become. In particular, certain tests such as calculation of the Lyapunov exponent need long time series to provide accurate results. Finally, chaotic analysis can provide better prediction as the methods applied are more advanced than those of the other linear and non-linear methods.

In addition, an interesting issue that comes out from the research is the need to look at the data in different time-scales. Daily data (as in any raw data set) is affected by noise. This noise may be caused by random incidents, such as a lorry breaking down or a driver being ill. The presence of noise in real data sets is always a limitation to the analysis of time series, especially in short-time series. However, these random events tend to be averaged out in the near future. As it is not desirable to remove data points it makes more sense to work with the data over longer a period to check how the structure of the data behaves.

1.6 Delimitations & Limitations

This research focuses on TPL providers that are experiencing high-level variability in their logistics demands. There are two limitations in this research. Both limitations are caused by the requirements of the methodological methods applied. Those are the type and the length of the data sets. Chaotic methods of analysis require time series data of no less than two years of daily inputs. The third limitation is related to the level of noise that is present in business empirical data sets.

1.7 Definitions

The definitions of the main concepts used in this thesis can be found in the Glossary provided at the end of the thesis.

1.8 Organisation of the Thesis

The organisation and structure of this thesis is divided into six main parts; introduction, literature review, research methodology, results, discussion, and finally conclusions and implications (Figure 1-1). The introduction provides a general overview of the study.

The literature review is composed of three chapters; elements of third party logistics, high-level variability in logistics demand and chaos theory. The purpose of the literature review is to present the theoretical background that the research is built on, to explain the link between the two individual fields of logistics management and chaos theory, and finally to provide answers to the first two research questions. Thus, the first chapter introduces the field of third party logistics and identifies the need to investigate the issue of high variability in logistics demand because of its impact on the efficiency of TPL operations. The second literature review chapter explores the potential sources of high variability in logistics demand, identifies the impact of these intense oscillations on TPL operations, and explains the necessity of investigating the application of a more advanced method to detect, analyse and anticipate this high variability, suggesting the direct application of chaos theory. The last chapter explains the main concepts of chaos theory and how the direct application can be beneficial to third party logistics management.

The purpose of the next part of the thesis, research methodology, is to present the process and method with which this research was executed and analysed. It involves two chapters; research design and data collection, and data analysis. The first chapter explains all the relevant processes and methods that were selected to execute and collect the data for this research.

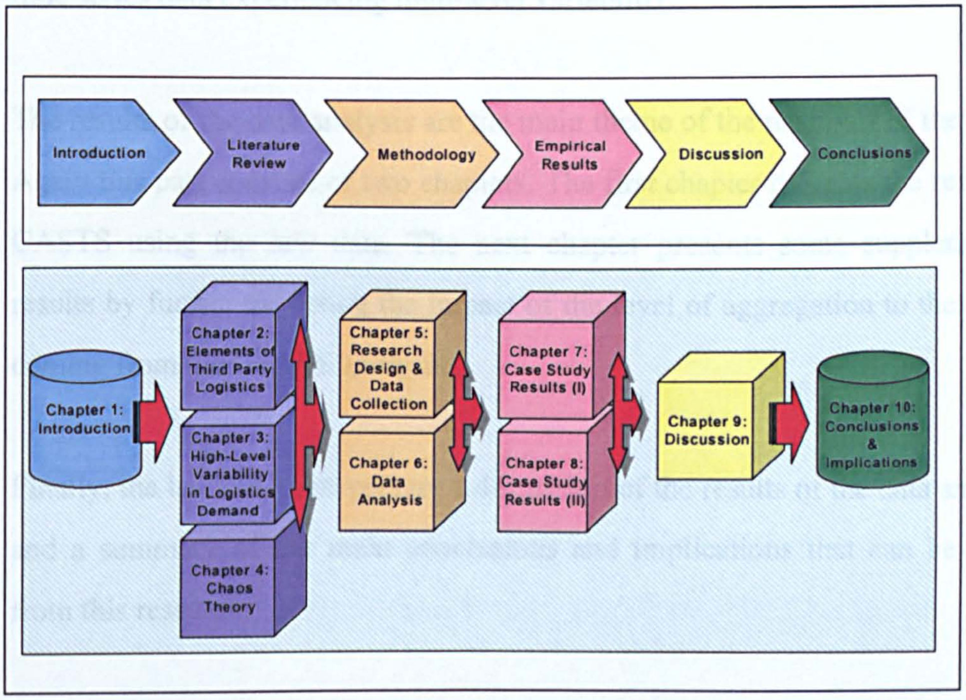

Figure 1-1: **Organisation of the Thesis**

In sequence, the second chapter thoroughly explains the philosophy and the mathematical details of the proposed methodological framework, the so-called CASTS method that was constructed by the author specifically to analyse short-time series data experiencing high-level variability.

The results of the data analysis are the main theme of the next part of the thesis. Again this part consists of two chapters. The first chapter presents the results of CASTS using the raw data. The next chapter presents some supplementary results by further exploring the impact of the level of aggregation to the results coming from the CASTS analysis.

Finally, the last two parts present a discussion of the results of the data analysis, and a summary of the main conclusions and implications that can be drawn from this research.

1.9 Summary

This chapter presented an overview of the thesis. Its purpose was to introduce the basic concepts of the research, such as the research problem and questions, the justification for the research undertaken, the methodology chosen, the main limitations and the key boundaries of the study.

PART II

LITERATURE REVIEW

Chapter 2:

ELEMENTS OF THIRD PARTY LOGISTICS OPERATIONS

Chapter 3:

HIGH-LEVEL VARIABILITY IN LOGISTISCS DEMAND

Chapter 4:

CHAOS THEORY

Chapter 2

Elements of Third Party Logistics Operations

Chapter 2

Elements of Third Party Logistics Operations

The purpose of this chapter is to provide the necessary theoretical background on Third Party Logistics (TPL) that will later be used as the basis for the implications of the research for both theory and practice. It begins with a general overview on TPL industry. Then, it proceeds in describing the main elements and functions of TPL. Next, the main challenges in TPL are identified and the challenge of future trends anticipation is prioritised. Finally, a summary of the key points of the chapter is given.

2.1 Introduction

The industry of third party logistics has seen substantial growth during the last couple of decades. In the 1990's factors such as market changes, new strategic directions, and changes in distribution activity (Buck, 1990) increased the complexities in the logistics function and encouraged the need for logistics outsourcing. It has been estimated that the TPL industry will grow 20% per year between 1999 and 2003 (Celestino, 1999). According to Amstrong this development offers greater opportunities for profitability and long-term logistics partnerships (Armstrong, 1999a). As a result, companies become more demanding. Third party logistics are expected to have the expertise to manage both the physical and informational flow around their own and their clients' networks. In addition, they are expected to have the transport and storage facilities in place, or available, and be able to offer a truly integrated and value adding set of services to their clients to solve their logistics problems and convert them into enhanced customer service opportunities. This new situation gives the opportunity for TPL providers to position themselves in their chosen supply chains and to become the preferred supplier of logistics services (inbound and outbound internationally) to major players in global markets.

Some facts about the TPL industry trends according to Milligan are (1) TPL services grew 16.5% in 1999 (2) total revenue for US-based third party logistics was $46 billion in 1999 (3) overall net profitability for the services was 5% and net TPL revenue was $25 billion in the same year (4) TPL providers are now looking at potential customers who have annual transportation bills of $1 million to $10. Until recently, $10 million has been the threshold for consideration by most TPLs (Milligan, 2000). In addition, the key market sectors that use third party logistics providers are the consumer (84%), computer (80%), chemical (70%), auto (69%), retail (68%) and finally medical (61%) industry (Langley, Newton & Allen, 2000). Furthermore, the impact of using third party logistics services to the companies are identified to be very positive in the logistics costs, logistics service levels, and customer satisfaction (Lieb & Miller, 2000). Finally, there are a lot of differences between American and European TPL providers. For instance, European TPL providers have a "growing interest in outsourcing of a broader range of logistics services, followed very closely by downward pressure on TPL prices" (Peters, Cooper, Lieb & Randall, 1998).

2.2 Overview of Third Party Logistics

The purpose of this section is to provide the necessary background on third party logistics. First, it defines the term *third party logistics*, and then proceeds to give brief historical evolution of TPL and continues with a short discussion on the current position of TPL in supply chains and finally, it identifies the current directions of TPL research.

2.2.1 Third Party Logistics Definition

There is no common definition for third party logistics. Several different terms carrying the same message have been introduced over the last decade. It seems to be a constant flow of new terms. Unfortunately not all of the new definitions are clear or precise (Gattorna, 1998). Some examples are logistics alliances (Bowersox, 1990; Bagchi & Virum, 1998), operational alliances in logistics (Andersson, 1995: Laarhoven, Van, & Sharman, 1994), contract logistics (Kearney, 1995; Africk & Calkins, 1994), contract distribution (Wilson & Fathers, 1989), and TPL (Lieb & Randall, 1996; Virum, 1993). Three examples of proposed definitions are given below,

> *Third party logistics services are multiple distribution activities provided by an external party, assuming no ownership of inventory, to accomplish related functions that are not desired to be rendered and/or managed by the purchasing organisation* (Sink, Langley & Gibson, 1996).

A relationship between a shipper and third party which, compared with basic services, has more customized offerings, encompasses a broader number of service functions and is characterized by a longer-term, more mutually beneficial relationship (Murphy & Poist, 1998).

Organisations use of external providers, in intended continuous relationships bound by formal or informal agreements considered mutually beneficial, which render all or a considerable number of the activities required for the focal logistical need without taking title (Berglund, 1997).

For the purposes of this research, considering all the pre-proposed definitions, including their weaknesses and strengths, the author defines third party logistics as:

Third party logistics providers are independent companies providing single or multiple logistics services to a purchasing company. Third party logistics providers, although they do not hold ownership of the product for distribution, are legally bound and responsible to perform the requested logistics activities of the purchasing company. The relationship between the two parties is long-term and beneficial.

2.2.2 The Role of Third Party Logistics in Logistics Chains

The current position of third party logistics in the logistics chains is vital. After defining TPL, it is necessary to position the TPL in the logistics chain. The logistics chain involves all the necessary logistics activities that are needed to transfer a finished product from its raw materials to the end customer. Companies' perception of the importance of the third party logistics role in logistics chains has changed dramatically in the last fifteen years. Factors such as globalisation of the market place increased the competition among companies, especially in the area of logistics. There are two main reasons for that; cost and reduction of lead times. Reduction in costs forced companies to produce in one place and yet sell in another. As a result the logistics chains started to become longer and more complex, requiring an "expert" to manage them. Complexity implies cumbersome management and high costs. Thus, as logistics chains become more complex the need for cost efficiency and speed becomes apparent and is the ultimate goal for all companies. The shift towards TPL has a positive effect on the logistics chains, buyers and suppliers, and the provider itself.

In general TPL play the combined role of a physical distributor, product flow co-ordinator, and service differentiator. In other words, the role of the third party logistics provider is to physically move the product from one place to another by co-ordinating and accommodating added value to the supplied logistics process and service. An added value can be obtained from the introduction of new services, such as bar coding, to more advanced services, such as logistics consulting, that result in reducing costs and increasing the efficiency of logistics function. Figure 2-1 shows the logistics chain processes, while Figure 2-2 illustrates the role of TPL between buyers and suppliers. It should be mentioned that it is possible that more than one TPL would be involved in more than one logistics activity. In that case, the complexity between the different actors participating in the same logistics chain increases exponentially, as more co-ordination between activities is required.

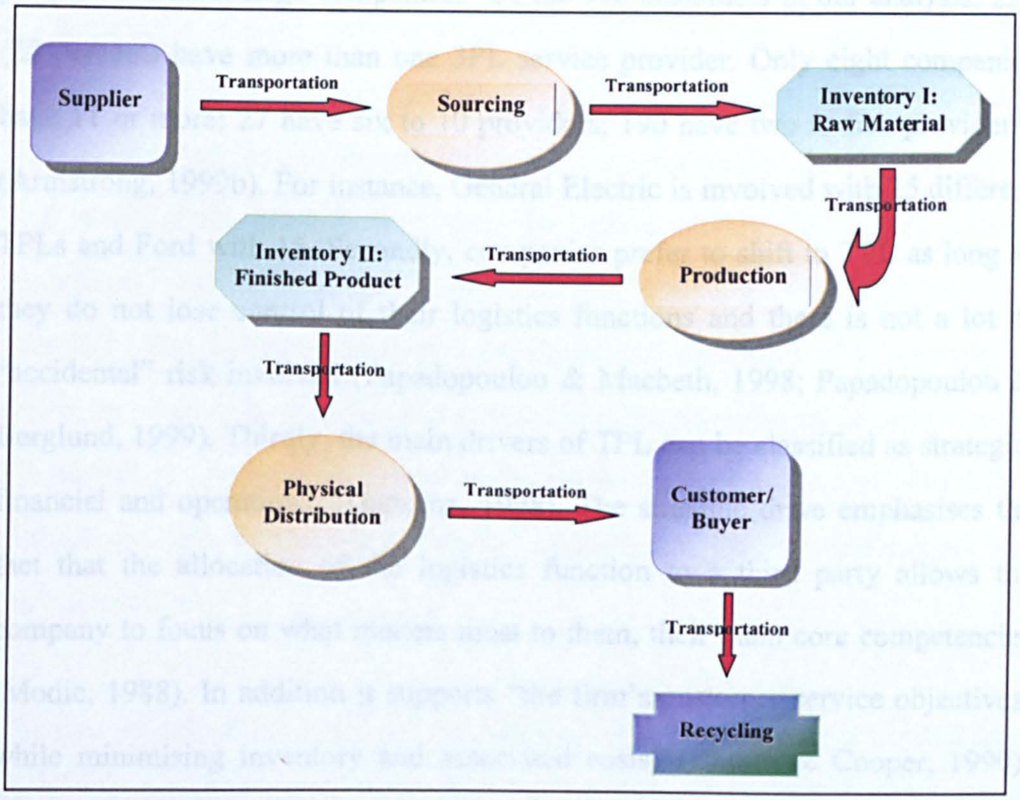

Figure 2-1: **TPL in the Logistics Chain**

This is a general description of a logistics chain. For instance, sourcing can be a logistics sourcing of its own right.

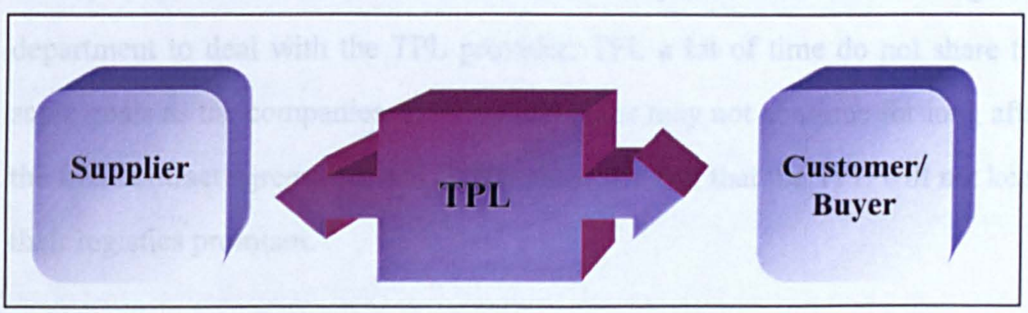

Figure 2-2: **TPL Relations with the Supplier & Customer**

The author identifies and summarises the following facts about the role of TPL in logistics chains. Firstly, it is unlikely there will ever be a single logistics provider for most large companies. "Of the 998 customers in our analysis, 221 (22 percent) have more than one 3PL service provider. Only eight companies have 11 or more; 27 have six to 10 providers; 190 have two to five providers" (Armstrong, 1999b). For instance, General Electric is involved with 25 different TPLs and Ford with 15. Secondly, companies prefer to shift to TPL as long as they do not lose control of their logistics functions and there is not a lot of "accidental" risk involved (Papadopoulou & Macbeth, 1998; Papadopoulou & Berglund, 1999). Thirdly, the main drivers of TPL can be classified as strategic, financial and operational (Gattorna, 1998). The strategic drive emphasises the fact that the allocation of the logistics function to a third party allows the company to focus on what matters most to them, their main core competencies (Modic, 1988). In addition it supports "the firm's customer service objectives, while minimising inventory and associated costs" (Ellram & Cooper, 1990). The financial factors are that TPL can reduce capital and supply chain costs. Finally the operational factor is that it simplifies the industrial relations environment.

Finally, the drawbacks of TPL are that companies still need a logistics department to deal with the TPL provider; TPL a lot of time do not share the same goals as the companies, the financial gains may not continue for long after the first contract agreement, and finally there is a risk that the TPL will not keep their logistics promises.

2.2.3 Historical Development & Growth[1]

A chronological analysis of strategic and logistics changes during the evolution of the demand of third party services (later TPL services) is instructive at this stage. The variables used to analyse the development are based on the world main events changes and are two; business strategies and logistics development. The world main events[2] determine the uncontrollable factors or external boundaries and opportunities affecting the company's logistics strategic planning. The business strategy[3] developments determine the controllable factors or internal boundaries and strengths of the potential third party clients. The logistics[4] development determines the need for third party services or TPL through the link between the external pressures of the strategic targets and logistics abilities.

The five periods of the historical evolution of TPL providers are generated from the chronological analysis and are: the introductory, awareness, necessity, integration, and differentiation periods (Papadopoulou & Macbeth, 1998; Papadopoulou & Berglund, 1999). Those reflect the main logistic and strategic alterations influenced by the principle world events (Table 2-1). These alterations were also reflected on the type of TPL services provided (Table 2-2).

Introductory Period

The introductory period covers the period from the early 1900s until the late 1950s. During this era turbulent geopolitical changes modified the whole

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[1] Part of this section has been presented and published in two refereed conferences (see Papadopoulou & Macbeth, 1998; Papadopoulou & Berglund, 1999).

[2] The analysis of the world main events is based on: Stearns, P.N. (1993) *The Industrial Revolution in World History*, Westview Press.

[3] The strategic evolution is adapted from Grant (1995).

[4] The logistics evolution is adapted from Kent and Flint (1997).

structure of the socio-economic world society. These movements brought rise to large organisations and created the need for contract management. This increased the demands on distribution movement and delivery response in order to satisfy the mass production and retailing demand. The logistics trends changed from the simple movement of goods to physical distribution as a separate function (McKibbin, 1987).

In the early 1900's, logistics was considered as a tool of marketing (Weld, 1916), while the first formal definition was given in 1927 (Borsodi, 1927). Company attitudes to logistics focused on the efficiency of physical distribution from the activities of transport, storage, inventory control, order processing and packaging.

In other words the development of the physical distribution concept is considered as an "emerging business issue" and began to attract strategic interest (Shaw, 1916) and created the total cost concept of logistics (Lewis, Culiton & Steel, 1956). Thus the world changes and the strategic push for cost efficiency stressed the importance of logistics through transportation efficiency. However the ownership and maintenance costs for the means of transportation increased as the trade activity increased too. Thus companies had to start considering the alternative of contract haulage.

This is the introduction period for the third party concept in the company's strategy. However the providers held full operational control and their services were restricted to the provision of transportation services.

Period	Description
Introductory	The concept of TPL is in its infancy. Companies do not consider third party providers unless there is a significant cost advantage or transportation shortage
Awareness	The concept of TPL gains popularity. Companies start to consider the third party alternative as inventory control and cost reduction pressures on the company's competitiveness and profitability increase. However, TPL still raises some concerns about the companies' loss of power and control over logistics
Necessity	The concept of TPL begins to be adopted by companies. The significant market and legal changes increase the distribution complexities that necessitate the assistance of a third party specialised in distribution
Integration	The concept of TPL interests more and more companies. The internationalisation and the augmented complexities of the distribution channels press companies to shift to third party distribution
Differentiation	The concept of TPL is considered as a differentiator in the company's competitive position. The globalization trend and the increased importance of partnerships and alliances as a way to increase competitiveness necessitate TPL as a vital function to support the companies' mission

Table 2-1: **The Five Periods of TPL Development**

Phase Period	Phase Name	Characteristic
Early 1900s - Late 1950s	Introductory Period	Single Services
Late 1950s - Mid 1960s	Awareness Period	Separate Services
Mid 1960s - Late 1970s	Necessity Period	Integrated Services
Late 1970s - Late 1980s	Integration Period	Combined Services
Late 1980s - Late 1990s	Differentiation Period	Complex Combined Services

Table 2-2: **Five TPL Phases**

The technological innovations of this period in manufacturing, vehicle and transportation networks played a catalytic role in the TPL development, as the movement of goods activity increased significantly. The general management attitude does not consider TPL's contribution to the company's profitability unless there is transportation shortage or cost advantage.

Awareness Period

During the late 1950s until the mid 1960s - the awareness period - important geopolitical changes took place. There was an increasing interest from the trade associations, companies and academia[5] towards the logistics function. The new logistics trends were the integrated logistics management (ILM) and the recognition of the significant differences between in-bound and out-bound logistics. Companies focused on physical distribution as a consolidation function for operational efficiency. However the operational efficiency is related to the third party logistics provider (Physical Distribution Forum 1972). The rationale behind this is that the market growth in relation to internal capacity shortages, capital and inventory control, and total cost trend, made it impossible for companies to be responsible for the transportation or warehousing ownership, maintenance, planning and control, with the result being a shift to outsourcing. Thus TPL started to stimulate company interest towards the benefits of logistics outsourcing.

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[5] The first logistics journals and textbooks came out during this period: *Transportation Journal*, Vol. 1, No. 1, 1961; *Logistics and Transportation Review*, Vol. 1, No. 1, 1964; Heskett, J.L., Glaskowsky, N.A. and Ivie, R.M. (1964) *Business Logistics*, New York: Ronald Press; Smykay, E.W., Bowersox, D.L. and Mossman, F.H. (1961) *Physical Distribution Management*, New York: Macmillan.

Necessity Period

The necessity period between the mid 1960s and late 1970s is characterised by major political, legal and financial changes. That, in combination with the revolutionary changes in technology (manufacturing, automation, etc.), information technology (IT), and escalating logistics costs concentrated the attention of the companies even more on third party logistics. Physical distribution started to be considered as a strategic alternative that could help to manipulate the economic uncertainties and contribute to the sales growth, and reduce the energy and transportation costs (Anderson, 1985). Hence, companies were interested in the creation of ILM to assist the total corporate function in improving the company's marketability. The logic was to improve manufacturing, marketing and financial results through the increase in customer satisfaction. In order to reduce the capital shortages, cost fluctuations and inventory (Cavinato, 1984) the concept of "make or buy" or sub-contract distribution was considered (Christopher, Walters, & Wills, 1978). The third party logistics services gradually increased in size, number, type of services and territorial coverage, and as such the first TPL contracts were beginning to appear (Berglund, 1997). Furthermore, TPL started to be considered as part of physical distribution and the make and sell function. The companies perceived TPL as an alternative to improve the distribution operations, cost effectiveness and achieve optimal cost and service situation (Fielding, 1974).

Integration Period

The main characteristic of the late 1970s and late 1980s is the internationalisation followed by continuous legal and economic adjustments. Sharman (1984) emphasised the need to rediscover logistics, as a result of the "shrinking of product life cycles, proliferating product lines, shifting distribution chains, and changing technology" (through the development of computer data handling). The deregulation, intermodalism, shipment control, and trade policies (Davis, 1987) increased the complexity of the trade and distribution channels. In addition the improvement in telecommunications and computers improved the efficiency and the control of the logistics function, allowing the development of the distribution function through complex global channels. The logistics concept was spread throughout management strategies and there was strong marketing and logistics relationships, as logistics became the way of achieving better customer satisfaction. Thus the new logistics trends focused on the international, and reverse logistics (Gattorna & Day, 1986). As a consequence the TPL providers were perceived as profit centres and differentiators as they contributed to better logistical operations. The rationale behind the TPL expansion was the business expansion that accompanied the increased complexity of the distribution channels, high export activity, technological advances, legal changes and globalisation trends (Buck, 1988). The TPL growth played an important role in the strategic management, and contributed to service and cost efficiency. Finally, it attracted the interest of academia (Wilson & Fathers, 1989). TPL was considered as a differentiator from the companies and not merely a necessity any more.

Differentiation Period

Global activity, major legal changes, modifications in trade and political blocks characterise the period between the late 1980s and late 1990s. Thus the new logistics trends were towards global logistics with the emphasis on reverse and environmental logistics through integrated material management (Busch, 1988). The application of expert systems encouraged the expansion of the logistics concept to the profitability contribution to the company (Spah & Novack, 1995). The marriage between marketing and logistics gained more and more importance (Lambert & Cook, 1990). Thus the new trends for logistics management were towards global logistics, contract logistics or logistics partnerships, marketing logistics "reliability - responsiveness - innovation" (Andraski & Novack, 1996), long term channel relationships (Geessenheimer & Robicheaux, 1996), and contract manufacturing (Crainic & Dejax, 1989). Thus the TPL was now considered to bring to the company economic, management and strategic advantages (Aertsen, 1993). The TPL services were continuously increasing in size and range of services. The supply was more than the company demand and the first signs of the intense competition in TPL market appeared. The improvement and the variety of the services they provided contributed significantly to the company's strategic planning and implementation as the world trade activity was at its peak. The distribution channels were becoming more and more complicated as the pressures from increased competition, international supply and distribution networks, corporate restructuring and high levels of expectation increased (Sheffi, 1990).

2.2.4 Current Research Directions

Third party logistics research often covers the logistics outsourcing area with descriptive and analytical studies on the pressures and benefits of logistics partnerships and alliance formulation and relationship maintenance. For instance, there are studies exploring the benefits of logistics outsourcing (Gill & Allerheiligen, 1996; Rao & Young, 1994; Aertsen, 1993; LaLonde & Maltze, 1992), partnership relationships and levels of satisfaction (Walton, 1996; Ellram & Hendrick, 1995), and managerial frameworks for better acquisition of TPL services (Sink & Langley, 1997). Finally, La Londe and Cooper (1989) contributed the first book focused exclusively on the partnerships in providing customer service from a TPL perspective, in which part of the research was on the design and implementation of a TPL relationship and the change of management.

Nevertheless, there are five main directions dominating the current TPL research. The author suggests that these research directions can be classified as third-party logistics trends, logistics outsourcing, channel & buyer-seller relationships and partnership and acquisitions relationships.

Third Party Logistics Trends

The first classification covers trends and the importance of TPL, highlighting their association with the manufacturer's activities (Anderson & Gillies, 1990; Sheffi, 1990). The main studies in third party logistics trends, on which several other studies are based, are focusing mainly on the American TPL market (Lieb & Miller, 2000; Lieb & Maltz, 1998; Lieb & Randall, 1997; Lieb & Randall, 1996a; Lieb & Randall, 1996b) and the European market (Peters, Cooper, Lieb & Randall, 1998).

Logistics Outsourcing

Outsourcing has been one of the strongest and most sustained trends in business over the last ten years. It has been supported by political ideology, management fashion, and short-term responses to recessionary pressures (Hendry, 1995), constituting cost reduction, knowledge and technology transfer as the leading outsourcing factors. General descriptions of the outsourcing phenomena can be found in Lieb & Maltz (1998), Peters, Cooper, Lieb, & Randall (1998), Razzaque & Sheng (1998), Lieb & Kopczak (1997), Lieb & Randall (1996) and Laarhoven & Sharman (1994). Sowinski (2000) gives a comprehensive list of vital questions that those companies wanting to outsource their logistics functions should consider before they select their future third party logistics provider.

However, early studies (or rather pre-1995) on TPL and logistics outsourcing are focused on the relationship between buyers and TPL providers (Bowersox, 1990; Virum, 1993; Leahy, Murphy, & Poist, 1995). Also, other studies have their focus on logistics outsourcing, especially improved customer satisfaction (LaLonde & Cooper, 1989; LaLonde & Maltze, 1992; Aertsen, 1993; Rao & Young, 1994; Gill & Allerheiligen, 1996).

Channel & Buyer-Seller Relations

This category includes analysis using the partnership and channel-buyer-seller relationship concept. TPL is examined through partnership characteristics (Ellram & Hendrick, 1995) and pitfalls (Ellram, 1995), levels of satisfaction (Ellram & Hendrick, 1995; Walton, 1996), and supply chain management (Ellram & Cooper, 1990). Whilst, other studies are centered on the articulation of the selection and buying process (McGinnis, Kochunny, & Ackerman, 1995), practical advice (Bagchi & Virum, 1998; Sink & Langley, 1997) and effective ways of managing TPL relationships (Boyson, Corsi, Dresner & Rabinovich, 1999). In addition further research has been focused on the managerial frameworks for better acquisition of TPL services (Sink & Langley, 1997), selection criteria for providers of third-party logistics services (Menon, Ginnis & Ackerman, 1998) and purely on buyer-seller relationships (Dahlstrom, McNeilly & Spah, 1996) and observational trends (Sink, Langley & Gibson, 1996). It has to be mentioned that most of the research has been approached from the shippers' (buyers of logistics services) rather than the providers' side. This seems to be changing as the providers approach becomes more recognized, currently due to the major consolidation forces acting within the TPL industry (Klaus, 1999; Hastings, 1999).

Partnership and Acquisition Relations

Other recent studies focus on investigating logistics relationships (Moore, 1998) and alliance & partnership issues (Bagchi & Virum, 1998). Although a few publications have focused on the logistics providers' strategies and development, which is the topic of this section, recent exemptions are Berglund (1997), Berglund, Laarhoven, Sharman, & Wandel (1999) and Cooper, Brown & Peters (1994), which discuss TPL providers' strategies, segmentation, and the TPL industry.

From the above categorisation it can be easily seen that most of the theoretical contributions to strategic logistics decisions borrowed from other disciplines. These are transaction cost approach (Skjoett-Larsen, 1994; Aersten, 1993; Ellram & Maltz, 1993; Maltz, 1993; Anderson, 1985), network perspective (Skjoett-Larsen, 1994; Halldorsson, 1998) and resource-based view (Halldorsson, 1998). However Mentzer and Kahn argue that, "much of logistics literature and research remains largely managerial in nature and lacks rigorous orientation toward theory development, testing and application" (Mentzer & Kahn, 1995). This thesis, as mentioned in Section 1.4, is directed towards filling the above gap by investigating the potential applicability of chaos theory to logistics management.

2.3 Third Party Logistics Operations

The purpose of this section is to identify the main elements and functions of TPL operations and how they are related to each other. Papadopoulou & Macbeth have illustrated how TPL, its elements and buyers and suppliers are interrelated with each other and exchange information (Papadopoulou &

Macbeth, 1999). Figure 2-3 illustrates the relationships that are developed in the system.

Despite the facts that the actors make unpredictable decisions, those decisions are not unrelated to each other. One affects the other as they feed back to each other. This section presents a review on the main elements and functions that compose the TPL operations.

2.3.1 Elements of TPL Operations

The most common logistics activities that are outsourced and formed the elements of TPL operations are transportation, warehousing, inventory management, and order management. As shown in Figure 2-4 these logistics elements are interrelated and influence each other in such as way as to remind one of a wheel. For that reason it is called the TPL operations' wheel. That means that a weak link within one of the elements will be amplified in the system and will be directly reflected on the efficiency of the other elements.

Transportation

Transportation is the logistics function that is responsible for the physical distribution of products from their place of origin to their destination. It is a factor of both place and time utilisation (Lambert, Stock & Ellram, 1999: 217). Third party logistics aim at providing this logistics function under the most optimum combination of fastest time and lowest cost. There are TPLs that specialise in a single mode of transport or a mixture of transportation modes. Those are motor, rail, air, water and pipeline.

Third party logistics can play the role of transportation broker, freight forwarders (domestic and foreign), shipper's associations or co-operatives, intermodal marketing companies (shipper's agents). The difficulty of the transportation function is that regulation issues, carrier costs, traffic management, and computer technology affect the level of sophistication in the analysis of the optimal routing. Transportation was the main function of third party logistics at the beginning of the last century. As the internationalisation and the globalisation increased, the logistics function of transportation became more and more complicated as well as more and more costly.

Therefore companies preferred to outsource the transportation function. Today outbound transportation represents 60.7% and the inbound transportation 44.6% among the activities most frequently outsourced and is expected to grow in the near future (Langely, Newton & Allen, 2000).

Warehousing

Warehousing refers to the storage of goods. It "is that part of a firm's logistics system that stores products (raw materials, parts, goods in-process, finished goods) at and between point-of-origin and point-of-consumption, and provides information to management on the status, condition, and disposition of items being stored" (Lambert, Stock & Ellram, 1998). In other words, it is related to place utilisation. Its main functions involve "efficient delivery and placing, cost-effective use of its space, adequate access to stored materials, security from theft and weather, proper stock rotation (e.g. first-in, first-out) [and] enough flexibility to deal with the largest (and smallest) items which will need storage in the numbers that will be needed" (Department of Trade & Industry, 1991). It is estimated that warehousing represents 63.3% of the most frequently outsourced TPL activities (Langley, Newton & Allen, 2000).

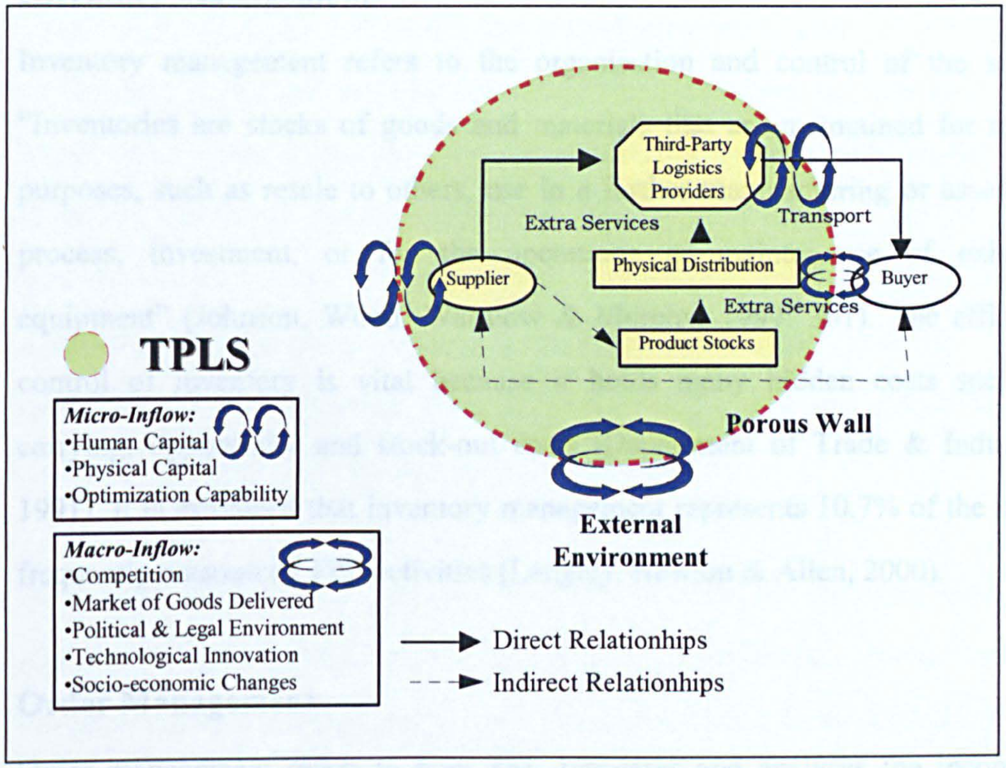

Figure 2-3: **Third Party Logistics System**

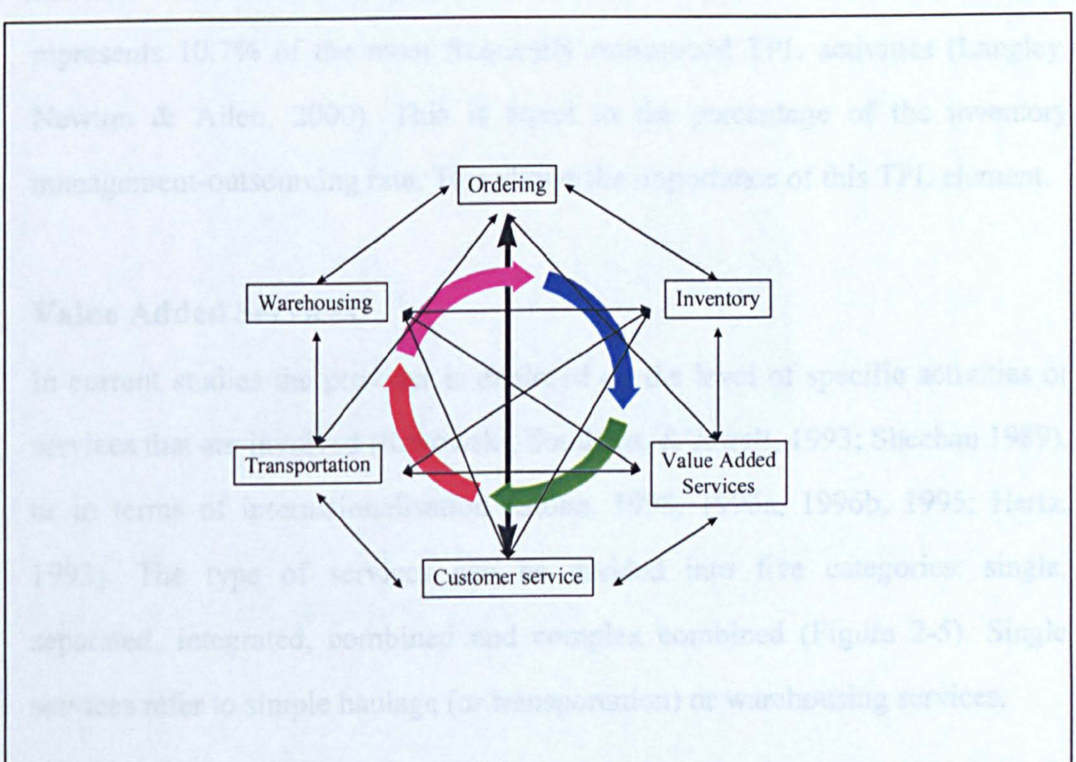

Figure 2-4: **Third Party Logistics Operations' Wheel**

Inventory Management

Inventory management refers to the organisation and control of the stock. "Inventories are stocks of goods and materials that are maintained for many purposes, such as resale to others, use in a further manufacturing or assembly process, investment, or for the operations or maintenance of existing equipment" (Johnson, Wood, Wardlow & Murphy, 1999: 301). The efficient control of inventory is vital because it holds many hidden costs such as carrying, opportunity and stock-out costs (Department of Trade & Industry, 1991). It is estimated that inventory management represents 10.7% of the most frequently outsourced TPL activities (Langley, Newton & Allen, 2000).

Order Management

Order management refers to how TPL processes and analyses the incoming orders. This element, besides its managerial aspect, is related to demand forecasting. When demand forecasting becomes an issue this element is directly affected. When order management is outsourced it is called order fulfilment and represents 10.7% of the most frequently outsourced TPL activities (Langley, Newton & Allen, 2000). This is equal to the percentage of the inventory management-outsourcing rate. This shows the importance of this TPL element.

Value Added Services

In current studies the provider is explored on the level of specific activities or services that are involved (Rakowski, Southern, & Jarrell, 1993; Sheehan 1989), or in terms of internationalisation (Stone, 1998, 1996a, 1996b, 1995; Hertz, 1993). The type of services can be divided into five categories: single, separated, integrated, combined and complex combined (Figure 2-5). Single services refer to simple haulage (or transportation) or warehousing services.

Separated services involve simple but unrelated services such as hauling or warehousing. Integrated services link the previous separated services and form simple distribution pipelines such as continuous warehousing to haulage deliveries. Combined services add extra value to the integrated services and form the logistics chains. These activities provide extra services on top of the equipment, warehousing, and transportation functions such as trade administration and planning services. Value added services (or complex combined services) form the logistics supply chains.

Third party logistics can provide pipelines of different services, such as planning, equipment, handling, yard management, warehousing, administration and information, and transportation functions (Rao, Young & Novick, 1993).

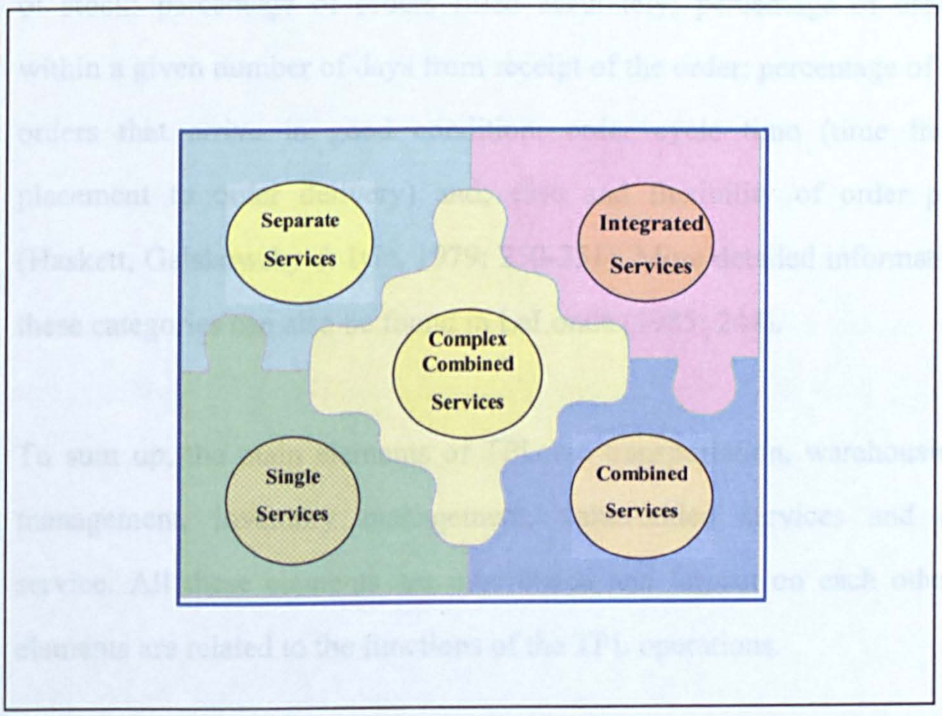

Figure 2-5: **Classification of TPL Services**

Customer Service

There are several definitions of customer service such as "customer service is a process for providing significant value-added benefits to the supply chain in a cost effective way (LaLonde, Cooper & Noordewier, 1988). Adopting the above definition for the purposes of TPL, a TPL customer service should be a process for providing significant value-added benefits to the logistics chain in a cost effective way. Therefore, inability to provide the promised logistics service will have an impact on the customer service.

Equally, if the delivered service is not economical, this will impact on both the TPL provider and the customer/buyer and supplier (Figure 2-2). In terms of logistics standards eight categories can be identified; time from order receipt to order shipment; order size and assortment constraints; percentage of times out of stock; percentage of orders filled accurately; percentage of orders filled within a given number of days from receipt of the order; percentage of customer orders that arrive in good condition; order cycle time (time from order placement to order delivery) and; ease and flexibility of order placement (Haskett, Galskowsky & Ivie, 1979: 250-251). More detailed information about these categories can also be found in LaLonde (1985: 244).

To sum up, the main elements of TPL are transportation, warehousing, order management, inventory management, value-added services and customer service. All these elements are interrelated and impact on each other. These elements are related to the functions of the TPL operations.

2.3.2 Functions of TPL Operations

The main functions of TPL operations are logistics forecasting, planning and control. Lawrence has related most of these functions in his logistics loop shown in Figure 2-6 (Lawrence, 1999). Looking at logistics it is apparent that the elements are related to each other and to the functions of the logistics system. According to the author the most important functions of TPL operations are logistics anticipation, logistics planning and logistics control. These functions are interrelated and affect each other as shown in Figure 2-7. It has to be mentioned that logistics planning and control, although affected by forecasting, forecasting is not affected by them. Forecasting results are independent of the way the management decide to use them. Nevertheless, the forecasting results determine the managerial decisions.

Logistics Forecasting

Logistics forecasting is possibly the post important TPL function. As shown in Figure 2-7, forecasting connects and affects both logistics planning and logistics control. As Lambert & Stock state,

> *The rationale for forecasting is twofold. First, proper logistics system control requires forward planning. Forward planning, in turn, requires good forecasts. The need for forward planning is greatest if the logistics executive wishes to keep the operations running smoothly; to adequately prepare for, and meet, future conditions and challenges; and to minimise present or potential problems in the logistics system of the company* (Lambert & Stock, 1993: 559).

In other words, "forecasts have become the base for decisions and action plans" (Gordon, 1998: 3). Closs *et al* emphasise the need for an integration of forecasting techniques, systems, and administration (Closs, Oaks & Wisdo, 1989). It is important that the selected forecasting technique is capable and

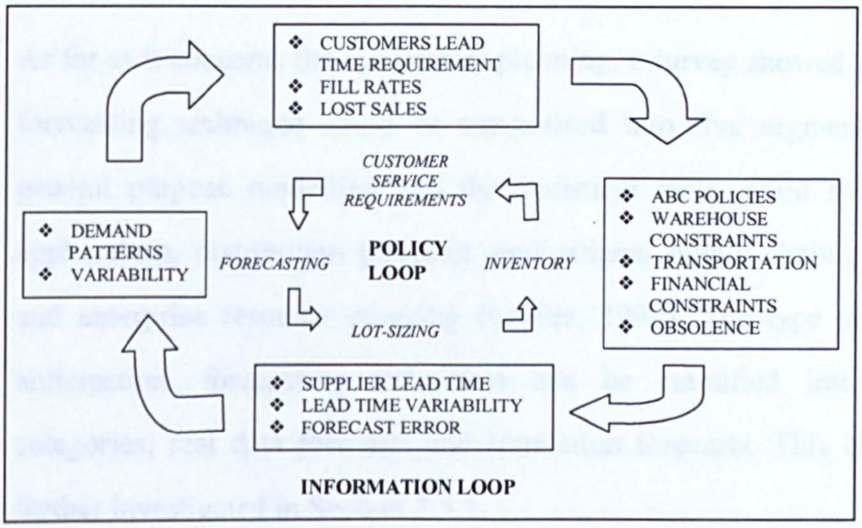

Figure 2-6: **The Logistics Loop**

Adapted from Lawrence, B.F. (1999). "Closing the Logistics Loop: A Tutorial," *Production and Inventory Management Journal*, First Quarter, Vol. 40, No. 1, pp. 44.

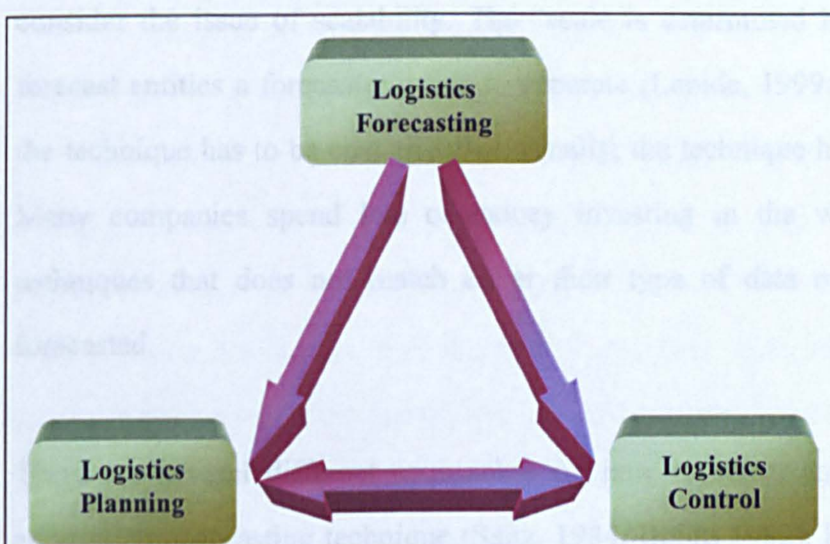

Figure 2-7: **Triad of TPL Operations**

flexible enough to capture the volatile nature of both the underlying data and TPL system.

As far as it concerns the operational planning, a survey showed that the type of forecasting technique could be categorised into five segments. Those are; general purpose modelling and the statistical tools, point solution forecast applications, distribution planning applications, supply chain planning suites and enterprise resource planning (Lapide, 1999). The type of data used in anticipation, forecasting techniques can be classified into two distinct categories; real data forecasts and simulation forecasts. This classification is further investigated in Section 3.5.1.

There are three main considerations in what make a forecasting technique worthwhile. These are identified as appropriateness, cost and accuracy (Seitz, 1984: 6). The selected forecasting technique has to be appropriate to the type of the data being investigated and to the item to be anticipated. Also it should consider the issue of scalability. The "scale is determined by the number of forecast entities a forecaster needs to generate (Lapide, 1999: 13). In addition, the technique has to be cost effective. Finally, the technique has to be accurate. Many companies spend lots of money investing in the wrong forecasting techniques that does not match either their type of data or the item to be forecasted.

There are several different approaches on how to select and implement the appropriate forecasting technique (Seitz, 1984; Boldt, 1982). However, Lapide, identifies three main features that each forecasting technique should have (Lapide, 1999). According to him an appropriate forecasting technique should have "(1) the forecasting features you need; (2) the scale of your forecasting problem, in terms of the number of forecasting entities (e.g. products and locations being forecast); and (3) the planning being supported (e.g. strategic, tactical and operational).

To sum up, logistics forecasting is possibly the most important function in TPL operations as it strongly influences the other two main TPL functions. As was, and will be further, explored in Sections 2.2.4 and in Section 3.5.1, the improvement of this function is the main issue examined in this study.

Logistics Planning

In general, logistics planning starts from the strategic level (customer service) and works down to the structural level (channel design, network strategy) functional level (warehouse design and operations, transportation and materials management), and finally to the implementation level (information systems, policies and procedures, facilities and equipment, organisation and change management) (Copacino, 1992). It is also divided into two types of strategic and operational level depending on the time frame for which the plan is intended. The strategic plan is intended to be at least a couple of years ahead, while the operational one is intended for a smaller timescale. According to the author the only difference between company logistics planning and a TPL logistics planning are the time frames that are involved in the plan. TPL planning is highly dependent on the intentions of their customers, which is reflected on their logistics demand as high variability. As those fluctuations most of the times are very intense, the operational logistics planning may have the duration of a few months or in some cases a couple of days. Similarly, the strategic planning may be reviewed every one or two years in order to match the highly volatile demands of the TPL industry and secure customer satisfaction.

Logistics Control

Logistics control comes from the evaluation and monitoring of the logistics performance and standards. Control allows the manager to determine the extent to which plans are fulfilled and guides the behaviour of organisation members towards the fulfilment of the organisation's goals (Novack, 1989: 8).

There are nine characteristics of control that were identified. Those are the degree of data aggregation, the reporting mechanisms, the degree of sophistication in setting standards, timing of data aggregation, variance causes identification, degree of measurement over time, degree of corrective action, level of managerial involvement, and type of corrective action (Novack, 1989: 10-18). All these characteristics are contributing to the level of success of the logistics control.

2.4 Current Challenges in TPL Operations

There are several challenges that third party logistics currently face. Armstrong has identified some optimisation features such as split-offs and filters, all-inclusive optimisation, mode conversion, constraints, speed, site location analysis, pool distribution, equipment availability, EDI and the internet and finally, transportation execution (Armstrong, 1999). Others such as Kopcza (2000) from Stanford University emphasise more the technological progress that allows TPL to provide new services, including co-ordination and integration service that "are necessary to support the complex new business processes that are being demanded."

The author has classified the current challenges in TPL operations in three main categories; industry dynamics, logistics flexibility, technological advancements and anticipation of future trends.

2.4.1 Industry Dynamics

As Lieb & Miller mention in their research one of the most important current TPL challenges is to understand the industry dynamics (Lieb & Miller, 2000). Industry dynamics are developed through external pressures, such as political and socio-economic changes, competition, and customer pressures. Section 2.2.3 explains in detail how these aspects affect the TPL industry.

Customer pressure is the next aspect of industry dynamics. Customer pressures are reflected on, and compose, the selection criteria companies use select to their TPL provider. Ackerman identifies thirteen selection criteria for third party logistics providers. These criteria assist in identifying the requirements of the industry, and are found to be; multiple warehouse facilities nationwide, inventory management and control, order acceptance and processing, pick-and-pack operations, order fulfilment, assembly – packaging and value-added activities, credit card verification, invoicing credit and collection, pre-sort capabilities, returns handling, manifesting, operational management structure, organisational strategic direction and finally financial stability (Ackerman, 2000). As a result all these criteria become the centre of attention for continuous improvement and therefore feed the industry dynamics.

Finally, competition is the last aspect of the industrial dynamics of TPL providers. Competition is focused on the increasing customer demand, described above, and on the effectiveness and efficiency of the service provided. It is not enough to provide what the customer wants if security about future performance is not guaranteed (effectiveness) or the price is too high (efficiency).

To sum up, it is vital for the TPL to be able to detect changes, opportunities and new trends in the way their customer and competitors operate. However, understanding the industry dynamics is one challenge, the next challenge is to implement and manage the proper logistics flexibility, which is needed to support these industrial dynamics.

2.4.2 Logistics Flexibility

The term logistics flexibility refers to the ability of third party logistics to adjust to its customer demands on better distribution accessibility, speed and low cost. According to the author logistics flexibility has two aspects to it; physical and managerial flexibility. For instance, it is not enough for a TPL provider to adopt the philosophy of "logistics flexibility" if its logistical infrastructure and structure are improper or inadequate to support such flexibility. That would gradually result in customer dissatisfaction and managerial distress.

Thus, the logistics flexibility challenge leads towards an enhancement of logistics capabilities, possible addition of services, integration and co-ordination of services, reconfiguration of activities and networks and strategic changes (Kopcza, 2000). Section 2.2.2 and Section 2.3 illustrated how all the logistics elements and functions are related with each other and in the logistics chain. Nonetheless, it is possible that these imperatives will require major new investments in information and logistics technology to ensure continuous improvements to achieve a competitive advantage.

2.4.3 Technological Advancements

As mentioned in Section 2.2.4 most of the literature on third party logistics relationships emphasis the importance of compatible communication/electronic links with their customers. The term technological advancements in third party logistics cover both areas of information technology, such as communication systems, and advanced logistics technologies such as robotics (Richardson, 2001). For instance, a lot of companies believe that to achieve daily optimisation in transportation management, EDI freight bill payment and other features that require sophisticated and robust software should be limited to TPLs (Armstrong, 1999).

Another example of electronic advancement is the increasing use of the electronic commerce. In his research Lieb reports that there is an increase in the interest of using E-commerce in third party logistics transactions. In the same research the CEOs of TPL responded facing some of the current challenges that the E-commerce are insufficient scale to support the necessary infrastructure, lack of client logistics expertise, unpredictable volumes, systems integration challenges, questions about the client's long-term viability, excessive risk and seasonality (Lieb, & Miller, 1999).

However, what should be mentioned is that technological advancement requires major structural changes and therefore compels high logistics flexibility. For instance, with the introduction of the internet, although before over 80% of products were transported in cases to shippers and wholesalers, now over 83%

of the outgoing parcels are shipped to the customers directly by taking full cases of the product but delivering small orders to the end users[6]. Gordon comments,

> *The 3PLs that will survive and prosper will be able to automate their business process, to connect with more purchasers and providers of transportation services, to expand value added services...the promise of such technology is to automate all essential back office tasks, improve business communications, and enable 3PLs to differentiate themselves competively by providing better information and enhanced value-added services to their customers* (Gordon, 2001).

2.4.4 Anticipation of Future Trends

The importance of good and accurate anticipation of future trends is not a new issue for third party logistics services. As Buck states, "but one of the secrets for a top third party operator is to anticipate the trends and requirements of a fast-changing distribution market" (Buck, 1990: 39). But why is it then that this challenge persists until now without being fully solved and that managers complain that their "forecasts are never accurate...[they] get the numbers and then we massage them to reflect more of reality"? (Cowper, 1998).

There are two main types of factors that can affect the efficiency of forecasting according to the author. Those are *controllable* factors, such as the level of appropriateness and understanding of the forecasting method, and *uncontrollable* factors, such as high-level variability. Lawrence states that "..if

[6]Anonymous (2001). "3PL Powerhouse," *Modern Materials Handling*, Vol. 56, No. 2, pp. 69-71.

an inappropriate method is used, results may be poor" (Lawrence, 1999). It is vital before any forecasting technique is applied to identify the type of underlying system to be examined (e.g. logistics demand). Also, the purpose of the forecasting technique should to be clearly defined before any further analysis is proceed. For instance, in the case of TPL it is vital to clearly define the expectations and the type of forecasting technique, as their logistics demand is strongly dependent on their customers' intentions and forecasting efficiencies and inefficiencies. Thus, any wrong selection in the forecasting technique may have tremendous effect on all the elements of TPL operations (Section 2.3). The benefit of the controllable factors is that they can be eliminated if proper attention is paid to them. However, it is not the same for the uncontrollable factors.

Many companies feel "turning to a 3PL is sometimes seen as a means of dealing with seasonality in demand" (Feary, 2000), because they cannot adequately perform their logistics activities. Thus, the question raised is "what if you are a carrier of critical shipments? How can a company plan around unforeseen emergencies in somebody else's business?" (Schwartz, 2000). Until now, although there have been some attempts to answer this question (Section 3.5.1) they have not managed to provide an adequate reply. For that reason this will be the purpose of this thesis, as stated in Section 1.2.

2.5 Summary

This chapter provided the necessary theoretical background of third party logistics to be used later to build the implications of the research to theory and practice. The general overview has shown that there is an increasing interest towards TPL research. The main reasons are the continuous growth of the TPL market and the vital importance that it plays in the logistics chains. The review of TPL operations revealed that all the TPL elements and functions are interrelated and affect each other in such a way that the anticipation of future trends in logistics demand is the leading function. In addition, the categorisation of the main current challenges in TPL also revealed that the current anticipation methods to forecast future trends in logistics demand are weak as a result of high-level variability and further investigation should be carried out. This identifies the main purpose of this study to investigate whether the new approach of chaos theory can improve the current ability to anticipate future behaviour of highly fluctuating data. The following chapter investigates further the issue of high-level variability in the logistics demand of third party logistics.

Chapter 3

High-Level Variability in Logistics Demand

Chapter 3

High-Level Variability in the Logistics Demand

The purpose of this chapter is to answer the first two research questions of this thesis. It is an extension of Chapter 2 and is based on a thorough literature review on demand variability. The discussion begins with a brief review of general literature on demand variability, then it proceeds to identify the main sources of high-level variability in logistics demand. The analysis continues by narrowing the discussion down to the demand variability in third party logistics followed by the identification of the impact of high-level variability on third party logistics operations. Finally, a discussion on current managerial approaches to manage these fluctuations is presented followed by a brief summary of the main points of the chapter.

3.1 Introduction

From the discussion of the previous chapter it is apparent that one of the main issues is how companies will manage "surge and uncertainty", or otherwise how they will respond to any unplanned rise and fall in demand (Copacino, 1998).

This chapter focus the discussion on the issue of demand variability in logistics demand. First, it tries to investigate what is demand variability, what are its main characteristics, and what type of research direction has been done before now. Having done that, the next question to be investigated is what are the main sources for demand variability and how are they related to third party logistics. Finally, the impact of these intense fluctuations to the operations of TPL and the current approaches taken to manage and moderate them are examined.

3.2 Demand Variability

Demand variability has been the subject of investigation for many different areas of management. For instance, in operations the impact of demand variability on inventory management has been of main concern (Bartezzaghi, Verganti & Zotteri, 1999), and in supply chains in relation to the stochastic demand of ordering policies (Cachon, 1999) and demand amplification (Chen, Drenzer, Ryan & Simchi-Levi, 2000). The main reason is the high impact that demand variability has on the operational, managerial and financial efficiency of the company's functions. Klassen and Rohleder comment that the main reasons managers struggle in this area are due to the pragmatic issues surrounding the forecasting of uncertain demand and the lack of integration between the operational function with the other functions of the company, such as a operation and marketing (Klassen & Rohleder, 2001). The purpose of this section is threefold; to define, classify and summarise the main research directions in demand variability.

3.2.1 Definition of Demand Variability

An important observation made from the literature review was that demand variability lacks a definition. Thus, the author defines it as follows:

Demand variability is a measurement of amplitude of oscillations within equal time intervals in the underlying data.

According to the amplitute of these oscillations, demand variability can be classified as low, medium or high level, depending on the patterns the oscillations define.

3.2.2 Characterisation of Demand Variability

There are five basic components used to define demand patterns. Those are average, trend, seasonal influence, cyclical movements and randomness (Krajewski & Ritzman, 1996: 454). The average gives information on the average value of demand – the total sum of demand entries divided by the total number of periods examined. The trend refers to demand directions over time – tendency for increase, decrease or stability of demand. The seasonal influence is the expected increase or decrease in the demand pattern as a result of a special period characteristic, e.g. Christmas rush. Cyclical movement follows the same concept as seasonality but it looks over longer periods of time. Cyclical behaviour can be influenced by factors such as product life cycle or national political status etc. The early identification of seasonality and cyclical behaviour is vital. However, cyclical behaviour is not always easily identified, as is explained later in this chapter. Finally, randomness or white noise implies pure unpredictability. In other words, there is no correlation between the demands of yesterday, today or tomorrow. All these components contribute to the characterisation of the demand variability.

Depending on which type of behavioural pattern, or combination of patterns, a data set appears to have the level of variability can be further classified as low, medium or high. A low level variability shows a single pattern of behaviour and is easily predictable. Medium level variability is a combination of a couple of different patterns of behaviour and its prediction is fairly easy. Finally, the high level variability combines more than two different patterns of behaviour and its prediction is difficult. The highest level of variability is randomness, where it is not possible to anticipate future patterns of behaviour.

3.2.3 Current Research

Accurate forecasting is possibly the most important element in logistics management. "Accurate forecasting is an important aid in effective and efficient planning and in controlling logistics activities...the best estimates of future demand, or forecasts, are usually arrived at from a combination of judgmental and statistical forecasting methods" (Tanwari & Betts, 1999). As a result, the leading research related to the detection, analysis and forecasting of demand variability is mainly directed towards the forecasting (other directions are discussed in Section 3.6).

Although current forecasting techniques can be classified into the three categories of time series, regression, and subjective techniques (Mentzer, Schroeter, 1994) most of the current research related to demand variability is coming from simulation modelling. Simulation has been mainly related to demand amplification research. The use of simulation as a vehicle of understanding issues of organisational decision making has gained considerable attention and momentum in recent years (Feigin et al, 1996; Kumar, Ow & Prietula, 1993; Malone, 1987). Towill, Maim & Winker (1992) used simulation techniques to evaluate the effects of various supply chain strategies on demand amplification. Tzfestas and Kapsiotis (1994) utilised a combined analytical/simulation model to analyse supply chains". Swaminathan, Smith &

Sadeh (1998) applied simulation to analyse and evaluate supply chain design and management alternatives using a multiagent approach. Forrester (1961) suggests faster order handling, elimination of one or more levels in the distribution chain, better sales data being made available to upstream players, exponential smoothing of inventory adjustments, and finally, timing of advertising campaigns to counteract rather than exacerbate demand oscillations. One difficulty with modelling approaches is when a given set of data is used more than once for the purposes of inference or model selection. Techniques such as data snooping are currently developing to avoid this (White, 2000). Finally, Gloss *et al* comments that, "the simulation models are designed to reflect the fact that the market demand and supply chain activities are dynamic processes" (Gloss, Roath, Goldsby, Eckert & Swartz, 1997: 24).

Finally, it should be mentioned that there is a new developing trend, although still in an embryonic stage - neural networks research. The essence of neural networks is that the initial model (or formula/equation) is made and then the system is left to develop by itself through learning from the continuous import of new data. The main strength of neural networks is that "they do not require any a priori assumptions regarding the underlying structure of the relationship they are estimating" (Zapranis & Ginoglou, 2000). According to Walczac, the main difficulties of this method are the selection of the appropriate variables and the capturing of sufficient quantities of training examples (Walczac, 2001).

3.3 Sources of High-Level Variability in Logistics Demand

Based on extensive literature review the author identified four main sources encouraging and contributing to high-level variability. Those are seasonal effects, external uncertainty, demand amplification, and random events.

3.3.1 Seasonal Effects

There are four seasonal effects[1]; seasonality, trends and cyclical events and irregular fluctuations (Chatfield, 1989; 9-10). Seasonality is nothing other than a variation that is repeated within a certain period of time. For instance, the consumption of ice cream is higher during the summer season than during the winter. "Trends" is a "long-term change in the mean level" (Chatfield, 1989; 10). For example, over the last 10 years it has been noticed that the consumption of ice cream has shown signs of significant increase. Cyclical change, on the other hand, is a certain behaviour that seems to be repeated within a certain time frame. For instance, the temperature levels of each month are different but they are repeated every year in a cyclical order. Finally, irregular fluctuations refer to any other type of variability effect that cannot be listed as a seasonal, trend or cyclical effect. Irregular fluctuations are normally listed under random effects. What has to be noticed is the fact that not all so-called "irregular fluctuations" are random. For that reason special attention should be paid to the source of those oscillations before any improper conclusions are drawn. The best example is the case of determinism and chaotic behaviour, which is the main topic of this thesis and is explained in later chapters.

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[1] Seasonal effects have a different meaning from seasonality.

3.3.2 External Uncertainty

External factors refer to factors that the company has no control over such as economic recessions, political incentives, etc. All those external factors first affect the companies' strategic plans and consequently influence the future behavioural patterns of demand, which in turn translates into increased variability in demand. External factors such as alliances, technological changes, cycle time compression, and the increasing competitive environment influence the variability (Meade & Sarkis, 1998). English identifies weather conditions and world events as two of the forecasting challenges (English, 2000). Crossan *et al* explains very well how the environment affects the companies and proposes techniques to shift environmental uncertainty to an opportunity (Crossan, White, Lane & Klaus, 1996). Competition is another external factor that can affect the demand variability because it influences the relationships between actors. In addition technological innovation is another factor that can create uncertainty, such as the introduction of E-commerce. Finally, new legislation or other political decisions can also affect the demand behaviour.

3.3.3 Internal Uncertainty

Internal uncertainty is generated from within the company itself from managerial and operational systems modifications that the company periodically undertakes. Managerial changes refer to alterations in planning and control either in the operational, tactical or strategic level (Cooper, Dickson & Innis, 1992). Operational decisions have a heavy financial orientation and deal with the planning and control of everyday tasks, such as management of order cancellations, etc. Tactical decision changes refer to decisions such as pricing schemes, advertising promotions, etc. Strategic decisions refer to the more general changes such as new corporate focus. Operational systems changes refer to any technological change, such as the introduction of a new software, or new warehousing technology. These type of changes feedback to the system and they influence the future behaviour of demand.

3.3.4 Demand Amplification

Demand amplification, or the bullwhip effect, is a dynamic and uncontrollable factor that develops within the supply chain and directly affects the levels of variability of demand. According to Lee, Padmanabhan & Whang (1997) the "bullwhip" effect can be defined as "the phenomenon where orders to the supplier tend to have larger variance than sales to the buyer (i.e., demand distortion), and the distortion propagates upstream in an amplified form (i.e. variance amplification)." Demand amplification "increases at each stage as demand, swollen by adjustments for inventories, supply lines, expectations, and anticipated profits is passed back from retailers to wholesalers, manufacturers of intermediate goods, and finally to capital and raw materials producers" (Sterman, 1986). It has been estimated that demand amplification tends to increase costs between 12.5% and 25% (Kurt Salmon Associates, 1993). The term demand amplification originates from Forrester's work on system dynamics in 1958. He "identified the existence of demand amplification and demonstrated its effects through the use of computer based simulations of demand variability along a distribution channel stretching form end-consumer, through retailer, distributor and factory" (Forrester, 1958).

Chen, Drezner, Ryan & Simchi-Levi (2000) assume two factors cause the bullwhip effect; demand forecasting and order lead times. Lee (1997) identifies four major causes. Those are demand forecasting updating, order batching, price fluctuation, and shortage gaming. Erratic patterns in demand cause the bullwhip effect, which is nothing other than small perturbations in downstream demand that are greatly exaggerated by the time their effect reaches the upstream supplier (Lapide, 2000). There are several sources of demand amplification such as inventory and backlog adjustments, lead times for capital, growth expectations and sufficiency of self-ordering (Sterman, 1986). "Rising orders deplete the inventories and swell the backlogs of capital-sector firms, leading to further pressure to expand" (Sterman, 1986). Table 3-1 summarises the main causes of demand amplification.

It has to be mentioned that demand information in a supply chain is often altered when transferred from one part or node of the supply chain to another. Lack of distorted information in demand requirements from one end of a supply chain to the other can lead to tremendous inefficiencies such as excessive inventory investment, poor customer service, misguided capacity plans, and ineffective transportation. It has been shown that information disruption increases the demand amplification exponentially moving up the supply chain. The most common symptoms of demand amplification are very short-term forecasting, and unrelenting amendments in planning and control mechanisms. This inefficiency could show up as excessive revisions of production plans and high corrective costs. "Additional amplification arises because the increase in customer demand and lagged response of production will boost prices, causing further expansion of orders and output as profits rise" (Mass, 1980).

3.3.5 Random Fluctuations

Random fluctuations refer to the type of oscillations that cannot be predicted, for instance, road accidents, earthquakes, etc. The main characteristic of those events is that they are normally suppressed in time by the system, unless they have a catastrophic effect on the system. Catastrophic is the effect that forces the system to undertake a sudden radical change that changes its whole function

	Causes of Demand Amplification
Forrester (1953)	• Decision logic of individuals responsible for demand management • Time lags between the transmission of information and materials • Short-term random fluctuations in demand • Limitation in production capacity in exaggerating demand due to over ordering in times of shortage • Advertising efforts
Lee (1997)	• Demand forecasting updating • Order batching • Price fluctuation • Shortage gaming
Sterman (1987)	• Misperceptions of time lags leading to over or under ordering • Lack of optimum stock levels by decision-makers at each point in the chain • Failure to plan for the required amount of stock in the pipeline when adjusting demand • False fluctuating demand a long the chain • Bounded rationality whereby decision makers try to optimise only their own element of the chain
Taylor (1999) [within automotive chain]	• Demand issues (external, internal demand) • Control issues (number of decision points, decision rationale, functional siloism) • Policy issues (financial pressure, inventory minimisation, JIT, price structure) • Supply issues (equipment reliability. Process capability, quantity variability, material indivisibility)

Table 3-1: **Causes of Demand Amplification Effect**

and in extreme cases possibly its nature.

3.4 Logistics Variability in Third Party Logistics

As mentioned in Chapter 2, one of the main characteristics of TPL is that the demand is directly dependent not only on the demand of their customers but on the demand of their customer's suppliers. As a result, TPL logistics demand is more inclined to experience high-level fluctuations. This is because their logistics demand is extremely sensitive to their customer's forecasting abilities and intentions, as third party logistics providers do not own the product, but act as intermediary services that execute their customer's logistics order.

Based on the discussion of Section 3.3, high-level variability in the logistics demand of TPL is created from both internal and external factors. Internal factors, such as implementation of new logistics decision support systems and information systems integration, impact on the traditional functional areas (Chapter 2) increasing customer performance expectations, and therefore are reflected on the logistics demand. "To reduce the impact of those uncertainties, supply chain managers must first understand their sources and the magnitude of their impact" (Lee & Billington, 1992). In addition, the historical review presented in Section 2.2.2 has revealed that external uncertainty in third party logistics can be created from six main sources; political, legal, economic, social, natural and technological. Any changes in any of the above areas will encourage competition and influence the customer's expectations as well as the TPL's ability to respond to these changes. This section is dedicated to explaining how the internal and external factors influence the level of demand variability in third party logistics by analysing the demand flow processes and dynamics raised within the supply chain (of customer, third party logistics and buyer companies).

3.4.1 Demand Information Flow within the Supply Chain

In the case of outbound logistics process, the demand information flow involves three main actors; the customer (or manufacturer) which produces the product; the third party, which undertakes the logistics services of the product, and; the buyer (or retailer) which purchases the product from the manufacturing firm. Similarly in the inbound logistics process, the demand information flow involves the same actors with the only difference being that the buyer is the supplier for the manufacturing company. In that case, the third party logistics is responsible to pick up the spare parts from the different suppliers and deliver them to the premises of the manufacturer for the production. The issues and dynamics developed in both cases are similar, and for that reason and clarity purposes the first scenario will be described here.

Figure 3-1 describes how the demand information flows within the supply chain, which is fully discussed later in this section. Briefly, the manufacturing firm has to forecast the demand of the retailer in order to plan its production and logistics operations. This forecasting is not only based on the future predictions of sales but also on the past records of the retailers ordering and inventory policies. This information is then imported into the master production planning, the results of which feed the logistics decisions. The manufacturing company after considering all the relevant logistics issues place an order to the third party logistics provider. The third party logistics provider, in sequence, processes the information and based on its logistics abilities informs the manufacturer on the distribution details. This information is then transported to the retailer and used for future reference as extra information on product receiving. In theory, cycle of demand information should be straightforward.

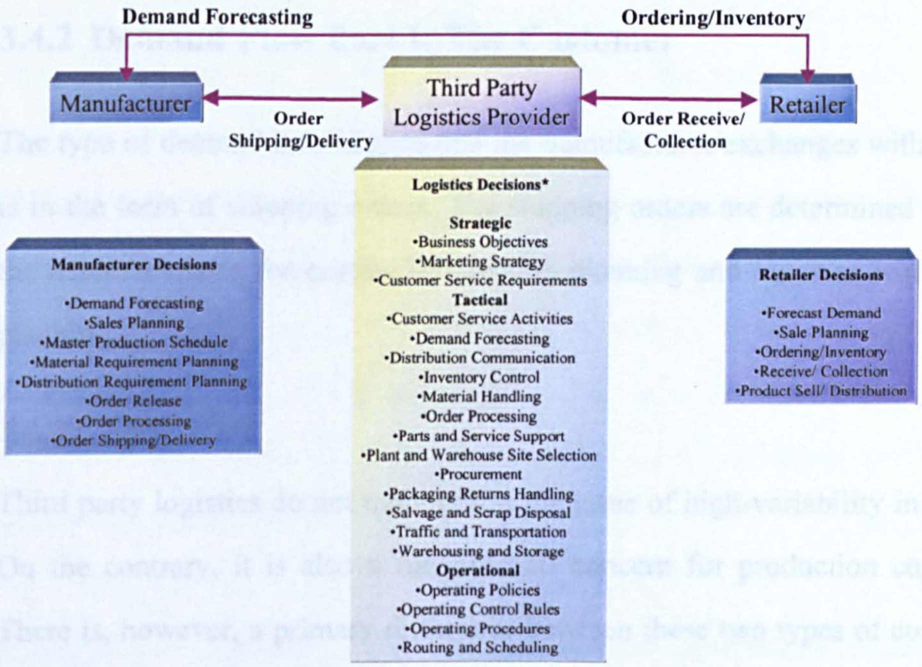

Figure 3-1: **Demand Information Flow in the Supply Chain**

*Adapted from: Lambert, D.L., Stock, J.R. & Ellram, L.M. (1998). *Fundamentals of Logistics Management*, McGraw-Hill International Editions, p.565.

However as previously mentioned (Section 3.3.), there are factors that increase complexity moving backwards to the supply chain increasing variability in demand. A description of the information process and flow within the supply chain is described below.

3.4.2 Demand Flow Part I: The Customer

The type of demand information that the manufacturer exchanges with the TPL is in the form of shipping orders. The shipping orders are determined based on the manufacturer's forecasting, production planning and logistics requirements planning.

3.4.2.1 Forecasting

Third party logistics do not monopolise the issue of high-variability in demand. On the contrary, it is also a fundamental concern for production companies. There is, however, a primary difference between these two types of companies; production companies produce and own the product, whereas third party logistics companies do not produce and do not own any their clients' products. As a result, production companies can generate several other internal types of data, such as marketing, sales, etc, that can complement and potentially improve the forecasted demand data. In the case of third party logistics providers, their clients' orders and, in some cases, information sharing with them is the only data they can rely to make their forecasts. For that reason, approaches presently used from production companies to improve the accuracy of their data cannot be successfully applied, as those discussed in Section 3.6, to third party logistics providers. Nevertheless, a glance over some current dominant collaborative supply chain approaches can be useful at this stage, as their understanding can offer useful information on the factors on which production companies base their logistics planning and are reflected as fluctuations on the their logistics providers demand data.

The first step in the production planning and control process is the forecasting or the estimation of what is going to happen in a future specified interval of time. Depending on the type of data, forecasting techniques are normally classified as subjective or objective. Subjective techniques include the sales force composites (Tull & Hawkins, 1993), customer surveys, jury of executive opinion (Makridakis, Wheelwright & Hyndman, 1997) and the Delphi method (Rowe & Wright, 1999). These techniques are all subject to high bias in estimation (Delurgio, 1998). For instance, the sales force may over or under estimate future demand trends depending on the individual salesperson's personality and/or his quota requirements.

The objective forecasting techniques are further classified, depending on the source of the forecasted data, as time series or causal models. Causal models base their estimations on the relationships between variables as opposed to forecasted time series. Econometric modelling is the main example of this type of forecasting. Although causal modelling is extensively used in economics it is not so commonly used in operations planning.

Operation planning mainly involves time series forecasting. Depending on the type of series there are several forecasting techniques. It has to be mentioned that identification of the type of series is as fundamental as applying the right technique, in order to get valid results. According to the most general classification, time series can be either stationary or non stationary. The techniques that are currently used for operation planning assume a stationary time series, *i.e.* a series in which each observation can be represented as a constant plus a random fluctuation. A stationary series, with no traces of trend or seasonality, can be estimated through a single or simple exponential smoothing, and simple or moving averages forecasting technique. If a trend is present, then either the regression analysis or Holts's method should be used. On the other hand, the seasonal decomposition using moving averages or Winter's method are more appropriate (Chatfield, 1978). Currently used forecasting techniques fall under the above classifications. However there is a lack of forecasting techniques, which can analyse high non-linear demand behaviour, such as chaotic behaviour. This is the type of data analysis on which this thesis is focused.

It has to be stressed that simply relying on naked forecasting estimation is not advisable in production planning, due to the rate of errors, which current forecasting techniques generate as a result of high variability. To overcome the large error issue research has focused on the development of collaborative forecasting philosophies incorporating other important issues that will make these estimates more complete. Their purpose is to optimise the collection of more accurate information, in order to improve the sales and profit rates. Commonly used techniques include collaborative planning, forecasting and replenishment (CPFR), value chain initiative (VCI), supply chain operations reference model (SCOR) and collaborative promotional commerce planning (CPC).

Collaborative Planning Forecasting and Replenishment (CPFR)[2]

CPFR proposes information collaboration between trading companies in order to increase mutual efficiencies and focus on common goals and measures. It is a

[2] More information can be obtained at (2002), http://www.cpfr.org/WhitePapers.html

"collection of new business practices that leverages the Internet, electronic data interchange (EDI), and SIL to radically reduce inventories and expenses while improving customer service". The purpose of CPFR is to reduce inventories and expenses while improving customer service. CPFR recognises different businesses's technological and organisational requirements, and proposes necessary changes to improve collaboration and meet mutual goals. The CPFR initiative is not new. Well-applied predecessors of CPFR include Efficient Consumer Response (ECR), Quick Response and Vendor Managed Inventory (VMI), which are discussed later in this section.

The CPFR process starts with an agreement between the trading companies to collaborate on their forecasting, planning and replenishment orders. Although each company uses its own production systems, the forecasting process is common. In this way, the supply chain system becomes a demand-driven system. The advantage of applying CPFR in a system is that it reduces forecasting uncertainty, improves inventory levels and allows quick response to demand changes. However, the main problem that CPFR suffers from is the limited number of companies that can participate in such a system. For example it works well in the case where three or even four companies are joined through CPFR, but it becomes virtually impossible when applied among 300 companies, which in many cases is the nature of the work for TPL. In addition, in certain cases, even though companies are joined under CPFR to minimise uncertainty in their demand, the demand can still be classified as chaotic. In this case, CPFR does not provide the right tools of data analysis, which is what the method of CASTS targets to improve.

Value Chain Initiative (VCI)

Microsoft developed the VCI in mid-1990s. The idea behind VCI is that if there is a standard tool that can guarantee information flow within the supply chain then the material flow will also be optimised. In other words, it provides a tool to avoid unnecessary replication of data and duplication of effort within the supply chain in order to reduce costs and improve margins for everyone involved. Mark Walker[3] comments, that "organizations around the world are very excited about the concept of dynamic data delivered in real time, which is the 'heartbeat' of the VCI."

There are six segments of VCI that are created in order to build structured data sets as a common denominator for companies to communicate and exchange information. Those are distribution management, transportation management, EDI and electronic commerce, import/export, inventory control, and warehousing management. The main focus of VCI is to serve the particular need of each customer. The optimisation starts with the de-construction of a demand signal, such as an order, into the constituent messages of that signal. The messages are sent to the appropriate party for planning and action. The end-product manufacturer is responsible for specifying the qualification parameters. The participant who can do it most efficiently is responsible to test and evaluate those parameters.

The main argument here is that this initiative provides real time data and minimises the replication of data within the supply chain but does not provide a method of analysis for the data gathered. If the nature of demand is chaotic then,

[3] The quote can be found at (2002), http://www.wpc-edi.com/Insider/Articles/V2/II-11n.html

this approach cannot change that and definitely does not offer a method of data analysis.

Supply Chain Operations Reference Model (SCOR)

The Supply Chain Council developed SCOR[4] in 1996. The purpose of SCOR is to provide an integrated, heuristic approach for supply chain improvement. The main argument of the SCOR model is that organisations that are focusing on supply chain performance from an integrated perspective experience improvements in virtually every phase of their supply chain. SCOR proposes establishing a strong link between the processes of re-engineering, benchmarking, and process measurement into a cross-functional framework. Much emphasis is placed on integrating the scope, operations strategies, and supply chain practices of each participant to the supply chain company. This can be achieved through the five main implantation steps. Those are planning, development, and formation of a company to support a new product line; re-engineering of supply chain processes to a corporation base; implementation of SCOR processes corporate-wide; re-organisation of logistics groups into plan, source, make, deliver concept; integration of multiple organisations through collaborative forecasting, and contract and purchase orders.

The benefits of applying the SCOR model can be summarised as; improves the delivery performance, inventory reduction, fulfilment cycle time, forecast accuracy, overall productivity, lower supply chains cost, fill rates, and finally, capacity realisation. However, the SCOR model fails again under the same criticism as the above models in that it can work well in a macro level but not

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[4] More detailed information about the SCOR model can be found in (2002), http://www.supply-chain.org/downloads/overview.pdf and (2002), http://www.concentus-tech.com/articles/refmodeloverview.pdf

when there is a large number of companies involved. In addition, although in the fourth iteration of the model and the integration of third party logistics providers is mentioned, it does not provide specific guidelines on how the TPL can integrate and forecast the large number of buyers or supplier that it services.

Collaborative Promotional Commerce (CPC)[5]

The Gartner Group and Aberdeen Group developed CPC as a product-centric business solution in order to enable the online sharing of product knowledge and incumbent business applications. CPC offers a global information sharing network, where affiliated companies share knowledge on product design, engineering, manufacturing and purchasing, sales and marketing, field services, and customers. The CPC examines both discrete and process manufacturing in the areas of collaborative product design; visualization (2D & 3D); manufacturability; outsourced manufacturing and engineering; sourcing, strategic procurement; supply chain planning, plant sequencing; inbound and outbound logistics including event monitoring systems; product field service; and support[5]. The main argument for applying CPC is that it can enable manufacturers to obtain important information that would allow them to create more competitive products in less time, at less cost, and with fewer defects than that of their rivals.

CPC, as with the aforementioned supply chain approaches, mainly improves the uncertainties of demand information within the supply chain, but does not provide the analytical tools to explore chaotic data.

3.4.2.2 Production Planning

In sequence, the forecasting estimates are used in the second step of the production planning and logistics process. According to Nahmias (1993: 106-

[5] More information can be found at (2002), http://www.aberdeen.com/

109) forecasting information is used to build the aggregate production planning (APS), master production schedule (MPS) and material requirement planning system (MRP). Aggregate planning involves decision making on two main issues in the production; the number of employees that the firms should retain, and the quantity and mix of products to be produced. The MPS specifies the exact amounts and timing of the production of each of the end items in a production system. Finally, the MRP forms the means by which the MPS is accomplished. Then the results of MRP are translated into specific shop floor and logistics decisions. It has to be mentioned that although the sequence of events is the same for all manufacturing companies, the systems used by the firms to accomplish those results may vary according to the philosophy of each firm. Some major examples of those systems and philosophies applied in the production planning stage include Material Requirement Planning (MRP), Kanban/Just-In-Time system (JIT) Optimised Production Technology (OPT), Efficient Consumer Response (ECR), Vendor Inventory.

Material Requirement Planning System (MRP)

There are two types of MRP systems; MRP and MRPII (Manufacturing Resource Planning). The purpose of both MRP systems is to put the results of the MPS into practice. The MRP system was introduced in 70s in order to computerise the inventory control system, calculate and schedule the demand for the raw materials needed for the production of the product. Simply, the MRP purpose is to work out what to buy and make from what you need (sold or plan to sell). More specifically, "an MRP system "believes" that the master production schedule, and the validity of outputs is always relative to the contents of that schedule" (Orlickly, 1975: 46). It is "a computer based production and inventory control system that attempts to minimise the

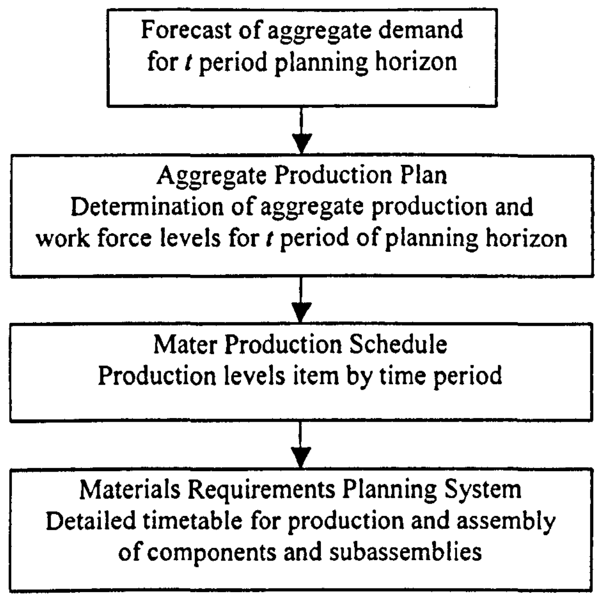

Figure 3-2: **The Hierarchy of Production Planning Decisions**

inventories while maintaining adequate materials for the production process" (Lambert, Stock and Ellram, 1998: 203).

The main outputs of MRP are "order-release notices, calling for the placement of planned order; rescheduling notices, calling for changes in open-order due dates; cancellation or suspension of open orders; item status analysis backup data, and; planned orders scheduled for release in the future" (Orlickly, 1975: 49). MRP involves exploding out a bill of materials and subtracting the on-hand balances, and lead times to work well.

There are three main concerns with MRP; it considers capacity last; uses fixed lead times, and; requires excessive reporting (Russell & Taylor III, 1998). In addition, it does not respond well to pull systems, as it is "push" based and production driven by a forecast demand. The MRP system requires high inventory accuracy of both parts and finished goods and do not act as agents of change for production planning. Also, MRP provides results for the company, which applies them. The efficiency of the operations of the trading companies is influenced by the effectiveness of their own production operations planning. Finally, it requires long term planning and therefore it does not work efficiently in quick response systems, which are relying on short-term planning.

The development of MRPII came later at the beginning of the 1980s. It started out as MRP and was mainly concerned with the ordering and scheduling of the materials, based on their inventory levels. Later the focus of MRPII extended to the whole manufacturing environment. The idea was to develop a system that could create answers to the "what if" question. In order to do that a link to the purchasing module along with the accounting, and production activity control module and with costing systems was introduced as manufacturing resource planning (MRPII). MRPII "includes the entire set of activities involved in the planning and control of production operation" (Lambert, Stock and Ellram, 1998: 204). One of the main criticisms of MRPII is that it is very dependent on the level of accuracy of the forecasting. Other issues raised are that inventory accuracy is vital; it is highly computer based; it does not influence the effectiveness of other production management issues, and finally, it is inflexible in the face of changes and fluctuations of the system.

When both systems are applied in a company the resultant system is known as closed loop MRP, as all the business processes are linked into a single integrated business system. More detailed information on these systems can be found in Browne, Harhen and Shivnan (1988), Orlicky (1974) and Wight (1974). Based on MRP information, manufacturing companies will process relevant information, plan their logistics and place their orders to the TPL.

Kanban/JIT Systems

The concept of Kanban and JIT systems made their appearance in 1950s. The philosophy behind the Kanban and JIT systems is that there should be zero inventories. In other words, there should be an interacting flow of materials in the system whenever they are needed, so that supply always equals demand. It is important to note that Kanban is only 5% of JIT (Russel & Taylor III, 1998). The idea behind Kanban is that parts and materials should be supplied at the very moments they are needed in the factory. In other words, it is closely related to the fixed-quantity inventory systems (Russell & Taylor III, 1998).

On the other hand, the role of JIT is to "extend Kanban, linking purchasing, manufacturing, and logistics...primary goals of JIT are to minimise inventories, improve product quality, maximise production efficiency, and improve optimal customer service levels (Lambert, Stock and Ellram, 1998: 197). It is a set of manufacturing techniques that serves to minimise inventory and maximise quality, flexibility and efficiency. The JIT idea was initially developed in Toyota automotive plants in an attempt to improve the efficiency of their manufacturing systems. The key word, and main concept in JIT, is zero. According to Edwards (1983) this reminds us of the main goals of JIT, which are zero defects, zero set-up time, zero inventories, zero handling, zero breakdowns, zero lead times, and finally a lot size of one. There are ten basic elements and twelve benefits of JIT system (Russell & Taylor III, 1998). The ten basic elements are flexible sources, cellular layouts, pull production system, Kanban production control, small-lot production, quick set ups, uniform production levels, quality at source, total productive maintenance, and good supplier network. Finally, the benefits of JIT can be summarised as reduced inventory, improved quality lower costs, reduced space requirements, shorter lead times, increased productivity, greater flexibility, better relations with suppliers, simplified scheduling activities, increased capacity, better use of human resources and more product variety. More detailed information about these systems can be found in Browne, Harhen and Shivnan (1988).

The main concerns with JIT systems are that they assume "pull" or demand oriented and production driven systems, and require a close supplier involvement. One element that this approach does not consider is the impact of a JIT approach on the third party logistics providers' capacity and response times. As this thesis will later prove, the manufacturer's demand patterns using the JIT philosophy show high level fluctuations (chaotic), which are difficult to analyse, especially with currently used forecasting and analysis tools.

Enterprise Resource Planning Systems (ERP)[6]

ERP is the "update of MRPII system with relational database management, graphical user interface, and client or server architecture" (Russell & Taylor III, 1998: 659). The purpose of ERP is to integrate and streamline the manufacturer's internal systems. The idea behind ERP is similar to MRPII but applied in more, so-called, multi-situations; multi-currency, multi-warehouse, multi-company, etc (Cullen, Webster & Muhlemann, 2001). ERP is intended to hook-up information along the supply chain and therefore replace the pre-established single information platform with enterprise-wide material, capacity planning and control relevant to trading partners. The production planning of ERP is based on a combination of actual and forecasted orders and the products are produced in large batches to gain efficiencies of longer production runs.

The implementation of ERP is very expensive and time consuming. It requires a mixed mode operation for an extended period of time. Also, ERP assumes that all the trading companies would agree to participate in this information sharing. ERP can be effectively used for the material requirements planning of long lead-time and production cycle products, with one-of-a kind production, and long term planning. However, although this approach provides in a way more clarity of information within the supply chain, it doesn't provide tools of data analysis that could capture high variability.

Optimised Production Technology (OPT)

The philosophy of OPT is based on planning around bottleneck production resources. It was introduced from the work of Goldratt, presented in his book the "Goal" (Goldratt, 1987). The idea is there should be no idle job in the

[6] More detailed information can be found in (2002), http://www.cio.com/research/erp/articles.html

system. If there is, the system flow should be balanced by using variable batch sizes and concentrating on optimising a plant's bottleneck resource. OPT system can be considered as an alternative to the MRPII, though it concentrates more on scheduling and shop floor control than planning. The goal of OPT is to increase profit by increasing throughput. OPT uses three main measures to achieve this; the throughput, inventory and operating expense. It looks at the whole company as a machine for making money and attempts to optimise the throughput of the system. The main idea is that the optimum of each sub-system is not necessarily the optimum of the whole system. Thus, OPT develops the concept of "bottlenecks" or constraints that exist in the system and whose inefficiency affects the profitability of the whole system. Therefore, these bottlenecks should be identified and eliminated. The way to achieve this is through factory scheduling. There are five main rules (Harrison, 1985):

- Balance flow not capacity
- The profitable utilisation of a non-bottleneck resource is not determined by its capacity but by some other constraint in the system
- Activation of a resource is not the same as the profitable utilisation of that resource
- An hour lost in the bottleneck is an hour lost for the total system
- An hour saved at a bottleneck is a miracle

One constraint of OPT is that although it can produce immediate results it requires a long time effort to sustain those results. The OPT targets "push" downstream from the constraint solution and "pull" upstream from the constraint solutions. It can operate finite capacity schedules and assumes stable environments. In the particular case of TPL, the capacity schedules are infinite and the environment is highly versatile. TPL providers operations are built on the notion of continuous infinite demand coming in from their customers. Unlikely manufacturing or retailing firms, TPL providers serve a large number of customers or suppliers under the constraint of high uncertainty in demand, as discussed previously in this chapter. As a result, the system complexity amplifies dramatically creating severe concerns on the harmonic organisation and coordination of TPL operations. OPT has been also criticised on the grounds of traditional cost accounting; requires simulation modelling of the process; needs good database, and; must go via one consultancy company (Harrison, 1985). The base of a successful simulation is directly related to how close to the reality the system analysed is represented. It is a fact that the more the constraints in a model building, the more difficult the representation of the system becomes. A good simulation model of a TPL system would require a vastly large number of different actors, using different operational, logistics and demand management processes, each characterised from different levels of uncertainties and requirements. All the demand needs of these nodes (actors) will have to be analysed and coordinated through their common TPL provider, considering the response of the supplier or retailer where the product is picked up or distributed to, on the logistics arrangement made from the coordinating actor of the triad, the TPL provider. Such a model representation would have been impossible and would have needed to be simplified. Therefore, would have not been any better from what is currently applied and would have raised the similar to the current issues. Finally, the adaptation of OPT should be seriously considered when scheduling complex resources (Pendlebury & Yeomans, 1985). However, as mentioned above, it is the nature of the TPL provider's situation that even the OPT approach does not capture the complexities of the extended range of demand creation locations in the customer and supplier network in which they operate. In effect, while users of the OPT approach argue that they can model and optimise the flow through the manufacturing unit they do not optimise the flow across the logistics network. More detailed information on OPT can be found in Brown, Harhen and Shivnan (1988).

Distribution Requirement Planning Systems (DRP)

The DRP system is the "application of MRP principles to the distribution environment" (Southern, 1997: 228). Within the Supply Chain framework, Distribution Requirements Planning (DRP) is the key subsystem for the planning and control of the distribution functions. Its goal is to ensure that the right product is at the appropriate distribution point at the right time. This may be better achieved by (a) Integrating distribution functions with manufacturing and purchasing systems (b) Enhancing management of finished goods inventory by measuring supply against actual and forecast demand for each individual supply centre and (c) improving utilization of transportation, warehousing and personnel resources. DRP is a function of determining the need to replenish inventory at branch warehouses over a forward time period. A time-phased order point approach is used where planned orders at branch warehouse level are exploded via MRP logic to become gross requirements on the supplying source enabling the translation of inventory plans into material flows. In the case of multi-level distribution networks, this explosion process can continue down through the various levels of regional warehouses, master warehouse, factory warehouse etc and become input to the master production schedule. The DRPII is the continuation of DRP, with the only difference being that it includes the key resources in a distribution system, such as warehousing, transportation, etc. In other words it is the extension of MRP into the planning of the key resources contained in a distribution system. It has to be mentioned that the forecasting made previously feeds the DRPII, which translates the forecast of demand to a replenishment plan. Thus, if the forecasting is not accurate then the logistics planning will be influenced. In reality, besides forecasting errors there are other issues that will influence the distribution demand, such as the inventory policies on safety stocks, the level of logistics outsourcing and finally, the buyers' similar logistics policies. The analysis of the DRP systems directly influences the TPL demand levels. However, the nature of DRP systems does limit their applicability on TPL operational organisation.

3.4.2.3 Production & Operation Philosophies - Discussion

The physical distribution involves the production of the raw materials from the different manufacturers, the distribution of those materials to the manufacturers premises for the production of the final product and finally the distribution of this product to the manufacturer's customers. The production of the manufacturer's product cannot start unless all the different raw materials needed are gathered. TPL providers are those responsible for the delivery of the raw materials or the distribution of the final product. The position of the TPL provider is unique in the sense that they are not suppliers and they are not customers. Therefore, other traditional approaches to minimise high variability fluctuations cannot work effectively. The main argument why not is summarised below:

Push (MRP, OPT, ERP) versus pull systems (JIT)

Push systems are following the concept of 'produce to sell'. They are therefore relying heavily on the accuracy of their operations schedules. The organisation of "push" systems depends on long-term planning, which allows longer response times for the trading points and distributors to react to the manufacturer demands. "Push" systems usually use production systems, such as MRP, MRPII, OPT and ERP, as they assume continuous production and long-term planning. "Pull" systems, on the other hand, suggest that the raw materials and parts are pulled from the back of the factory towards the front where they become finished goods. So, in the pull systems the production follows the same rate as the placement of the customer orders. The implication that this type of system creates is that ordering becomes more and more complex towards the raw materials end of the supply chain, as response times becomes smaller and tighter. In some ways, the companies reduce this complexity by adopting a push approach, which allows more inventory control to face the variability in demand. This does not help TPL providers, however since they are highly likely to experience high variability in their logistics demand. Thus, TPL providers feel the pressure to plan an efficient and effective system that will respond quickly to those fluctuations, under the burden of extremely short response times and the co-ordination of hundreds of suppliers or retailers. The TPL providers need techniques to identify patterns of behaviour and aid the creation of potential scenarios that would allow TPL providers to plan their logistics operations more effectively and efficiently.

Focus on single firm performance (MRP, MRPII, OPT)

Most of the production and operations philosophies focus on improving the production efficiency of the underlying company that applies them. Even the extension into ERP with its intention of looking into the networks of suppliers to coordinate manufacturing schedules does not allow for the customer service, JIT approach of the major customer to be effectively translated into logistics schedules for the TPL intermediaries. Their application does not influence the processes of the related trading companies. The information generated from the production and operations systems has to be further processed by the logistics department and then this information has to be further analysed and imported to the TPL(s) system.

Limited response time and large number of input resources

One argument that could be raised is why TPL providers do not apply a collaborative approach to solve the fluctuation problems in their demand. The answer is that collaborative techniques have not been applied efficiently to a large number of companies. TPL providers have to deal with hundreds of trading companies and respond under very short time frames. Also, these collaborative techniques assume that all the trading companies apply a uniform information technology that allows real time data flow. Even if that was feasible, the time to respond to demand orders is so small that the TPL providers wouldn't benefit. It is also a feature of the complex interactions involved that the system behaviours create complex patterns and of itself a collaborative approach between even a number of nodes would not cover enough of the system stimuli.

Limitations of forecasting analysis

In the case of high-level fluctuations, it is highly probable that the type of demand pattern may be chaotic. In this case, current methods of analysis both traditional and non-traditional do not incorporate a method of analysis that could efficiently analyse the data and provide good insights for TPL providers to use in order to plan and improve the cost and quality of services.

3.4.3 Demand Flow Part II: The Third Party Logistics Provider

The manufacturer has to decide the quantities to ship to its customers (retailers) based on the analysis of the production planning of the company. The third party logistics provider then, receives the orders on how much product has to be shipped to the retailer. The process of the logistics planning in the third party logistics would have been similar to the operational planning of the manufacturer excluding the master production-planning phase, as the TPL is a service and does not produce a product. The issue however raised at this stage, which this thesis addresses is how to organise the forecasting in such a way that high variability can be minimised and therefore better planning can be achieved, allowing high flexibility. The notion is the same as in the manufacturer's forecasting phase. Forecasting collaboration could be an option and works well in the case that the third party logistics company does not have to co-ordinate the distribution of several different products to a large number of retailers. The same logistics applies to the inbound logistics, *i.e.* when a third party logistics provider has to co-ordinate the pick up from several different suppliers to the manufacturer. In these two particular cases, the forecasting and planning of the distribution for a third party logistics provider becomes cumbersome and inflexible. The TPL provider then has to proceed to the traditional methods of data analysis: time series analysis. The behaviour of the demand can be linear or non-linear. In the case of linearity there are forecasting problems. In the case of non-linearity forecasting performance depends on the level of non-linearity. For low and medium levels of non-linear data there are numerous traditional methods that can be applied and have been proven to work well. However, in the case of high non-linearity, and particularly in the case of chaotic data, traditional methods of analysis do not capture the deterministic behaviour and treats it as random. The company then misses the opportunity to recognise and analyse its demand. This is the issue that this thesis addresses. What can a company do in this case? The methodology presented in this thesis assists companies to better analyse and forecast their demand.

3.4.4 Demand Flow Part III: The Buyer

As described in Section 3.4, the buyer company(s) influences the demand forecasting of TPL in two ways. First, when the customer company has a collaborative forecasting with the buyer company or when excess product is returned back, or in the case of inbound logistics fewer products than originally planned is given out. These two factors are not however influencing the forecasting of the TPL.

3.5 Impact of High-Level Variability to TPL Operations

As mentioned in Chapter 2 one of the main challenges of TPL was to improve the anticipation of future trends in logistics demand. The main reason for that issue was the fact that current forecasting tools seem to be unable to capture intense oscillations in the logistics demand. Consequently, it can be concluded that the efficiency of the current forecasting methods is low for that type of behaviour. Lummus and Vokura state that, "current systems which use forecasts of demand to drive activity in the supply chain must be re-evaluated. Forecast adjustments can mean significant changes in production schedules and, unfortunately, many forecasters don't realise the impact that forecasts can have on the supply chain" (Lummus & Vokurka, 1999).

In Chapter 2 it was shown how the main elements and functions of TPL operations are interrelated and influence each other. Klassen and Rohleder comment that, "the pattern of demand influences decisions about day-to-day scheduling, promotions (e.g. a lower price during a slowing period), and other short-term aspect" (Klassen & Rohlede, 2001: 4).

It was explained that the level of efficiency in forecasting directly affects the efficiency of logistics planning and control, which in turn determines the operational efficiency of the main elements of the TPL operations. The author classifies the impact of high-level variability in logistics demand in TPL operations in three different levels; operational, managerial and financial (Figure 3-3).

3.5.1 Operational Impact

The first level that high-level variability impacts on the TPL operations is at the operational level. The elements of TPL operations that are affected are transportation, warehousing, ordering, inventory, value added services and customer service, as presented previously in Chapter 2. Those areas are affected in their transportation inefficiency, warehousing inefficiency, longer order cycles, inventory inefficiency and, longer lead times.

Transportation Inefficiency

The anticipation of future trends in logistics demand is directly related to the level of transportation efficiency. Many TPL providers complain about how their trucks are always either half loaded or too few to cover the demand. Forecasting is the function that determines the future transportation planning and control. In other words, transportation decisions are dependent on how many items are requested for transportation. Barker identifies three types of transportation decisions. Those are transportation service, such as modal choice, purchasing of transportation service, such as tariffs, and finally, resources, such as facilities, equipment and staffing (in Lambert & Stock, 1993: 216.).

Inventory Inefficiencies

Another area affected is the inventory management. High demand fluctuations result in inventory inefficiencies in the form of out-of-stock or excess of stock. Davis comments that, "inventory exists more or less as simple insurance against uncertainty... [and] the more variable the orders, the more stock required to reliably meet customer demand" (Davis, 1993: 38).

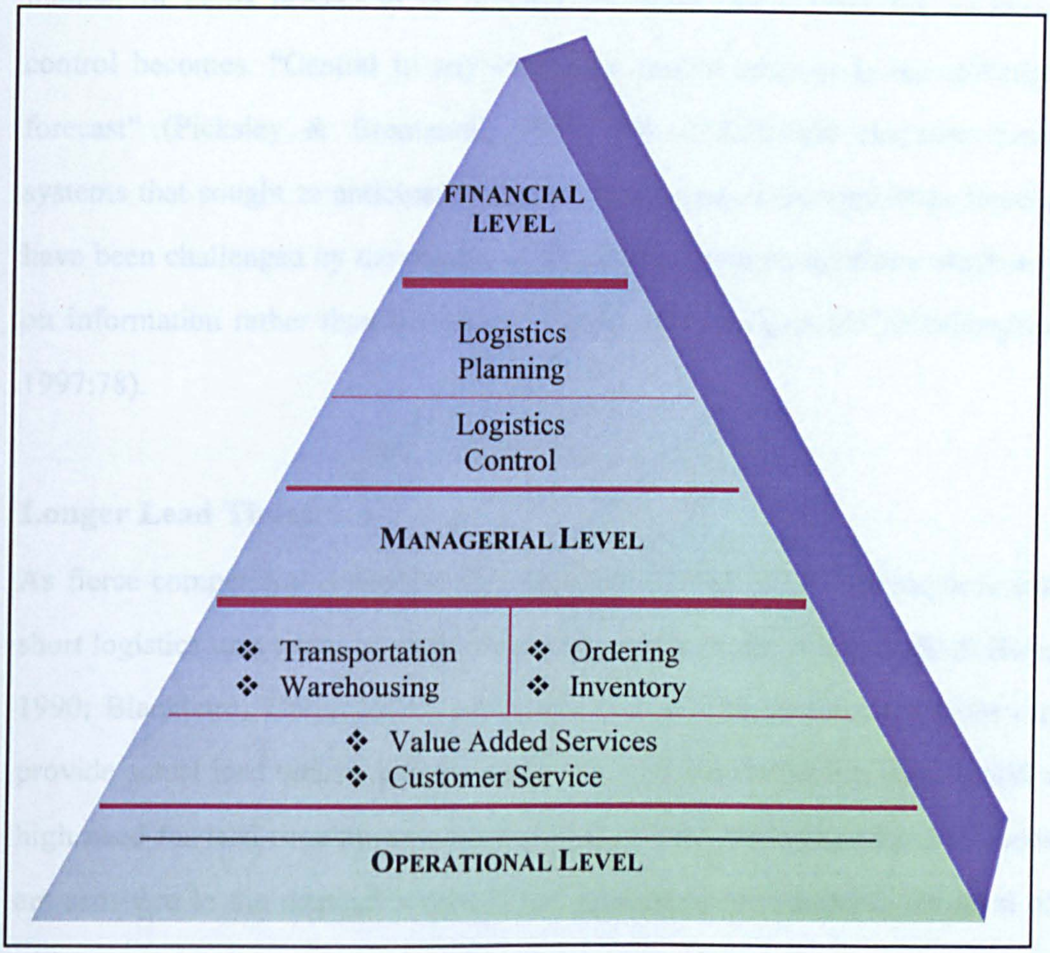

Figure 3-3: **Impact of High-Level Variability on TPL Operations**

Also the inventory efficiency is particularly sensitive to demand variability (Bourland, Powell & Pyke, 1996). Thus, whenever there is variability or uncertainty in demand the inventory control suffers. In addition, the larger the number of items needed to be ordered the more complicated the inventory control becomes. "Central to any inventory control systems is the statistical forecast" (Picksley & Brentanall, 1999: 19). "Traditional inventory-based systems that sought to anticipate customer requirements through sales forecast have been challenged by the advent of JIT, quick response solutions which rely on information rather than inventory to meet customer's needs" (Christopher, 1997:78).

Longer Lead Times

As fierce competition penetrates the market more and more, fast response and short logistics lead times becomes vitally important (Stalk, 1988; Stalk & Hout, 1990; Blackburn, 1991). Luber comments that as long as the competitor can provide actual lead times while the customer is still on the phone, there is still a high need for lead time improvement (Luber, 1990). Unfortunately, lead times are sensitive to the demand levels. If the demand is very unstable the level of efficiency will decrease. Christopher distinguishes two different types of lead times in the supply and logistics chains, the "horizontal" and the "vertical" time (Christopher, 1997). He defines as horizontal the time that is spent during the process, such as in-transit time and order processing time. Vertical, on the other hand, is the "still" time during which the product is part of the inventory.

3.5.2 Managerial Impact

Companies that are experiencing high variability in their demand, usually have to use very short time forecasting, in some case daily forecasting. In extreme cases, the concept of forecasting does not even apply anymore, as the error is higher than the actual prediction. As a result, since accurate forecasting is not feasible and the short-term prediction is more likely to be achieved, operational planning is emphasised more and more.

If this is not clear then the planning will suffer. Heskett *et al* has classified the service strategies based on the predictability of demand (Heskett, Sasser & Hart, 1990: 146), as shown in Table 3-2. In addition, demand variability has severe impact on the planning of global logistics systems (Vidal & Goetschalckx, 2000).

"Long-time business strategies can only be planned if each business action has a limited number of predictable outcomes...hierarchies and short term planning are needed to run day-to-day operations, the long-term future must be allowed to emerge from the self-organising activity of loose, informal destabilising networks. The fatal weakness of international strategies is that they are relatively inflexible plans for wholly unknowable futures" (Lloyd, 1995: 18).

Quick Fix or Severe Amendment Control Approach

Control is merely based on the quick fix or severe philosophy approach. That means that companies either will use emergency approaches to cover extra transportation or will proceed to extremes such as changing completely the information communication. In some other cases companies are so desperate they will be willing to try any method available that promises to solve the problem of high variability in logistics demand.

"When customers' demand fluctuates randomly from day to day, one strategy to consider is demand-responsiveness routing; that is, redesign delivery routes each period to match the demand of that period" (Haughton & Strenger, 1998).

Predictability of Demand			
		Unable to Predict	*Able to Predict*
Ability to Shift Customer Demand	*Low*	"Chase" demand with capacity or lose business	Plan supplies to meet fluctuating levels of demand or lose business
	High	"Chase" demand with capacity or inventory demand (through reservations and queues) where capacity is fixed	Manage demand through service design, communications, distribution, pricing, or inventory methods as well as plan supplies to meet fluctuating levels of demand

Table 3-2: **Classification of Strategies According to the Level of Predictability of Demand**

Adapted from: Heskett, J., Sasser, W.E. & Hart, C.W. (1990). *Service Breakthroughs*, NY: The Free Press.

Other approaches are to change the philosophy of their logistics chain by participating in the demand chain philosophy by creating alliances with those best able to fulfil consumer's needs and wants (Blackwell & Blackwell, 1999).

3.5.3 Financial Impact

Finally, demand variability has a financial impact on the TPL operations. Demand variability tends to increase the total costs (Jordan, 1987). Research has shown that the demand variability increases the total variable cost of the optimal schedules for various lot-sizing algorithms (Jordan, 1987).

3.6 Current Approaches to Manage High-Level Variability in Logistics Demand

After an extensive literature review the author suggests that there are four main approaches that third-party logistics undertake in order to moderate high-level variability in logistics demand. These approaches are forecasting integration, demand management, information integration, and demand driven or "pull" approach.

3.6.1 Forecasting Integration

Forecasting integration is a relatively new concept. However, more and more companies seem to be keen to shift towards forecasting integration (Mentzer & Kent, 1999; Gordon, 1998). There are two reasons for that; the collection of historical records is not enough if it is not accompanied by extra information on what the customers' plans are and; the forecasting method is not sufficient if it is not related with the company's operations.

In literature there are only a few main research papers that propose forecasting integration in order to increase the accuracy of anticipation. According to the author the most important is the multiple forecasting system (MFS), which proposes the integration of forecasting techniques, systems and administration (Mentzer & Schroeter, 1994). The philosophy behind this approach is that by combining the three main categories of forecasting (time series, regression and subjective) the benefits of each approach will be combined and will provide a more flexible "forecasting" method. Another example is the collaborative planning, forecasting and replenishment (CPFR) which takes a holistic approach to the supply chain management among a network of partners who are co-operating in the above three levels (Sherman, 1998). Finally, multi-tier forecasting is another proposed technique to improve forecasting, which again uses multiple data sources in order to capture the supply chain dynamics (Lapide, 2000). As discussed earlier these approaches are not complete enough to 'solve' the TPL provider's problem.

3.6.2 Demand Management

The main goals of demand management are to increase demand or smooth demand (Klassen & Rohleder, 2001). Demand management "encompasses forecasting, order entry, order-delivery-data promising, customer order service, physical distribution, and other customer-contact-related activities" (Vollmann, Berry, Whybark, 1992: 318). Demand management captures and monitors the logistics data and then categorises it depending on the logistics services that it has to go through, such as warehousing, transportation, etc. It has to be mentioned that it is vital for the success of the logistics efficiency to use the right type of data for each logistics activity that is to be performed. For instance, the total logistics demand, that is coming in as the total number of orders requested for distribution (and is investigated in this thesis), should not be used for the calculation of the inventory planning and control. A list of currently available software for demand management can be found in Gracking and Dobrin (1997).

3.6.3 Information Integration

Forrester was one of the main figures who explained the issues that can be raised by lack of information sharing (Forrester, 1961). Lee (1997) proposes information sharing, channel alignment, and operational efficiency as solutions to the bullwhip effect. There are a few supporting investigations to empirically prove a link between information sharing, integration and supply chain performance (Gloss, Roath, Goldsby, Eckert & Swartz, 1998; Daughrty, Ellinger & Rogers, 1995; Gustin, Daugherty & Stank, 1995; Daugherty, Sabath & Rogers, 1992). Since then, more and more companies focus on information sharing in order to minimise the effect of demand variability on their planning and increase their operation's efficiency. As a result, a new style of relationship between entities in the logistics chains based upon a more open sharing of information emerges. In this way, instead of each actor having to anticipate requirements on the basis of forecasts, the aim is now to become demand driven. (Christopher, 1997: 81).

3.6.4 Demand Driven or "Pull" Approach

One approach is to develop the logistics competency of "agility" and to avoid the necessity of forecasting as much as possible (The Global Logistics Research Team at Michigan State University, 1995: 183-215) regardless of the fact that even in agile companies there are situations where forecasting is needed (Pfohl, Cullmann & Stlözle, 1999). According to Lummus and Volura, "to compete in the future, companies must learn to "pull" products through manufacturing to distribution to customers, in the right amounts and in the right assortments, when needed. In essence, companies should manage the "demand chain" rather than pushing products through the supply chain" (Lummus & Vokurka, 1999).

3.7 Summary

The purpose of this chapter was to identify the sources and the impact of demand variability in third party logistics. It was found that the sources of high variability could be classified in four main categories. Those are trend or variability effects, external factors, internal factors of the system factors and random events. Those factors can affect the demand either individually or in any combination. As a result, the high fluctuations minimise the effectiveness of forecasting, inventory control, logistics planning, and customer service and maximise total logistics costs and lead times. The current approaches to tackle this issue are mainly focused on improving forecasting methods and techniques, increasing data sharing and integrating logistics functions.

Overall the conclusion is that none of the techniques discussed in this chapter are yet able to provide a robust solution to the problems faced by the TPL provider operating in a complex web of multiple customer demand points, multiple suppliers and variable order patterns changing in short time scales.

Chapter 4

Chaos & Chaos Theory

Chapter 4:

Chaos & Chaos Theory

Over the last decade, physicists, biologists, astronomers and economists have created a new way of understanding the growth of complexity in nature. This new science, called chaos, offers a way of seeing order and pattern where formerly only the random, erratic, the unpredictable – in short, the chaotic- had been observed.

(James Gleick, 1987)

The purpose of this chapter is to introduce the main concepts of chaos theory and outline the fundamental insights emanating from the study of chaos. It is divided into four main sections. The first section provides the background of chaos theory and chaos. Initially, it reviews the development of chaos theory in both natural and social sciences. Then, it defines scientific chaos and describes its main attributes. The second section identifies and analyses the causes of chaos. The third section elucidates which systems are prone to chaos and summarises their main attributes. Finally, the last section points out the main issues raised by the application of chaos.

4.1 Introduction

The development of complex sciences during the past decade has seen a rapid growth, especially in the area of management, financial and economics sciences. The main reason for this growth was the need to explain events and systems that appear to have a rather unpredictable behaviour. Chaos and complexity theory are the two most widely studied theories specialising in this issue. The main reason is that they provide the theoretical and mathematical tools to investigate and analyse the functions of complex systems. The main reason of their rapid growth is their revolutionary theoretical framework, which allows the examination of complex structures, which cannot be investigated using traditional theoretical methods. Before the emergence of complexity theory, the unpredictability of such systems was attributed to randomness – a non-deterministic time series that can only be analysed using probabilistic statistics. The application of complexity theory revealed hidden structures that were not possible to be observed previously. Although the mathematical background of both theories coincides the theories themselves focus their examination on different angles.

Complexity theory suggests that systems are self-organised, independent entities with the ability to co-adapt to their surroundings. These systems form simple relationships and processes that allow them to progress to discernible entities. Also, the theory supports that, no matter how simple the structure of a system is, that system incorporates complex functions. Some of the areas that complexity theory focuses are fitness landscapes, self-organization, emergence, self-organized criticality, and emerged relationships. Complexity theory has been related to information sharing in order to examine relations and newly formed systems. Information includes any possible element that is exchanged between two or more systems and contributes to the self or new development of a system. Information trade is the fundamental element for any systems' growth. Without this element "swap," the system will become isolated and gradually die.

On the other hand, chaos theory looks at the underlying patterns and relationships between events. The basic belief is that apparent disorder may incorporate order. Also, chaos theory proposes that even the tiniest change can be amplified within the system and cause big effects. In comparison to complexity theory, chaos theory examines information transfer through "memory" and "patterns of behaviour" non-linear mathematical tools. Chaos theory is more mathematically oriented than complexity theory, and for that reason complexity theory is more widely applied in the examination of management and business systems' behaviour and relationships. While, chaos theory is more widely applied to the quantitative analysis of those systems. This chapter is dedicated to the description of the theory of chaos.

4.2 Chaos Theory Definition

Many times chaos theory has been called "art". It implies "a kind of inherent *uncertainty principle* - not just in how we perceive the world but in how the world actually works." (Cartwright, 1991: 45). Chaos theory is not "concerned with describing a final stable behaviour of a system" (Buriando, 1994). According to Gleick "chaos is more directed at describing the manner by which a system chooses between competing options" or technically described as bifurcations. Considering that almost all systems are open - in other words, liable to exchange information and elements with nearby systems - these birfucations become so complicated that they make the final state of the system rather indeterminable. Chaos theory can be used to "provide means for understanding and examining many uncertainties, non-linearities, and unpredictable aspects of social systems behaviour" (Kranser, 1990). It deviates from the traditional approaches of analysis, in that it provides an alternative way of thinking. Chaos theory is:

> *...a general term for theories and ideas being generated in separate scientific disciplines like physics and biology that do not exactly conform to classic Newtonian scientific explanation* (Overman, 1996).

Gleick adds:

> *Where chaos begins, classical science stops. For as long as the world has had physicists inquiring into the laws of nature, it has suffered a special ignorance about disorder in the atmosphere, in the fluctuations of the wildlife populations, in the oscillations of the heart and the brain. The irregular side of nature, the discontinuous and erratic side -- these have been puzzles to science, or worse, monstrosities.* (Gleick, 1987: 3)

4.3 The Historical Development of Chaos Theory

Chaos theory from 1892 until the present has been developed dramatically, one of the main reasons being the development of computer advancements (Radzicki, 1990: 58). From its applications in physics and mathematics it has been extended into other natural sciences, and it has been adopted both as an analogy and as a metaphor[1] in social sciences. In natural sciences, for instance in engineering, examples of the direct application of chaos theory can be found in vibration control, stabilisation of circuits, chemical reactions, turbines, power grids, lasers, fluidised beds and combustion (Ditto & Munakata: 1995). The next two sections discuss the evolution of chaos theory in both natural and social sciences.

4.3.1 Chaos Theory in Natural Sciences

The origins of chaos theory can be traced back to late 19th century in natural sciences. Physics and mathematics set the background for the construction of the theory. Other natural sciences such as ecology, meteorology, and medicine followed, making significant contributions to the building of the theory. Social or soft sciences followed later.

This section aims at describing briefly the evolution of chaos theory and its infusion into management in order to present the increasing need for this theory in management.

The fundamental question "is the solar system stable?" posed in an astronomy competition by King Oscar II of Sweden in 1887, was the trigger for the development of chaos theory. Seeking the answer, Henri Poincaré was the first to view the presence of dynamical chaos in the solar system, recognise dependence on initial conditions and invent topology as a new brand of mathematics (Stewart, 1989). This was enough to attract the attention of many researchers from a wide range of different disciplines to try to investigate and solve the mystery of chaos. In 1892, the Russian mathematician Lyapunov come up with the concept of Lyapunov Characteristic Exponents to quantify the

[1] For further explanation about the interactions of analogies and metaphors from natural to

average growth of infinitesimally small errors from initial points. Later the mathematicians Birkoff (1927), Kolmogorov (1941), and Cartwright & Littlewood (1949) made advances in the mathematics of chaotic dynamics, with Smale formulating a plan to classify all the kinds of dynamic behaviour (Smale, 1967). In meteorology, Lorenz (1963) developed the concept of unpredictability in weather systems. He explained that fluctuations create small errors that are magnified significantly as time passes, altering the final result momentously. He captured this concept in the most famous question "Can the flap of a butterfly's wing in China stir up a tornado in Texas?" known as the "butterfly effect". Furthermore, in the 1970's Ruelle suggested that turbulent flow may be an example of dynamic chaos (Ruelle & Takens, 1971). In ecology, May made a significant contribution with his paper on simple mathematical models with very complicated dynamics (May, 1976). Later, Feigenbaum (1977), worked on turbulence and phase transitions and came up with the discovery of universality, known as the route from order to chaos. At the same time, along with the advance of computer capabilities, Mandelbrot analysed the geometry of fractals in computer graphics and image compression, giving a new dimension to chaos theory applicability (Mandelbrot, 1977).

4.3.2 Chaos Theory in Social Sciences & Management

Natural sciences monopolised the applications of chaos theory until the 1960's when social sciences started to be interested in the possible appropriateness of chaos theory. Fortunately, the rapid advancement of computer power and "the incorporation of system dynamics simulation modelling into institutional analysis [which] among other things add precision and mathematical rigor to the institutionalist pattern modelling process" (Radzicki, 1988) encouraged the

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social sciences see Cohen (1994) and Cohen & Nagel (1962).

introduction and expansion of chaos theory into social sciences and management (Table 4-1). As Kiel said "with the focus of chaos theory on non-linearity, instability, and uncertainty, the application of this theory to the social sciences was perhaps a predictable eventuality" (Kiel, & Elliott, 1997: 2).

Most of the applications of chaos theory can be found in organisational systems and politics research (DiZirega: 1989, Grossmannt & Mayer-Kress: 1989, Sestanovich: 1993, Thiétart & Forgues: 1997). In psychology, it was used by Allen & McGlade to study human systems to show the difference between "Cartesians" and "Randomisers" (Allen & McGlade, 1987). In sociology chaos theory is used in metaphorical and poststructuralist usages (Young, 1991).

Yet, the field of management was the last to utilise chaos theory. Without direct reference to chaos theory, Forrester made primitive steps towards it in his book *Industrial Dynamics,* where he challenged the traditional beliefs of equilibrium and linearity (Forrester, 1975).

Nevertheless, it would be reasonable to nominate Jantsch (1980) as the "father" of chaos theory in management, as he was the first to directly apply chaos theory to analyse organisational systems. Other applications can be found in the areas of control, prediction and non-linear dynamics (Young & Kiel, 1994), internal dynamics (Neumann: 1996), and strategic leadership in health management (McDaniel: 1997).

Year	Name	Area
1965	Emery & Trist	Social Science
1980	Jantsch "Father" of Chaos' Intro to Management	Management: Organisational Systems
1987	Allen and McGlade	Psychology: Human Systems and "Cartesians" and "Randomisers"
1988	Adams "Father" of Intro Chaos in Organizational Interactions	Management: Social Interactions in Physics-Equilibrium (Pigogine)
1989	DiZirega	Politics: Social Democracy and "Spontaneous Order"
1989	Grossmannt and Mayer-Kress	Politics: Dynamics of International Arms Race, Non-linearity and War
1989	Kiel	Public Administration: Organisational Upheaval as Positive - Non-equilibrium
1990	Daneke	Public Administration: PA and non-linear Dynamics and Self-organising Systems
1993	Sestanovich	Politics: Demise of Soviet System and Conventional Wisdom -"Oscillations and Unpredictability"
1993	Kiel	Public Administration: Outputs of State Oklahoma Proved Chaotic
1994	Young and Kiel	Management: Control, Prediction, and Non-linear Dynamics in Management
1994	Kiel	Public Administration: "Practical Theory" on Non-linear Dynamics for USE
1996	Neumann	Management: Internal Dynamics and Relationships with External Environment Review
1997	Thietard and Forgues	Politics: Action Structure and Chaos - Asian and USA Conflict
1997	McDaniel	Health Management: Strategic Leadership

Table 4-1: **Chaos Theory & Its Incorporation into Social Sciences**

4.4 Definition of Chaos

Chaos theory has been the subject of a multidisciplinary investigation for a long time now. Contrary to most theories, it does not originate from the contribution of one "father figure" but rather from the contribution of many researchers coming from a wide range of different fields. As a result, chaos does not have a single definition but rather many similar definitions depending on the type of discipline in which chaos theory has been examined. Li and York (1975) gave the first formal mathematical definition of chaos. Since then, there have been several different but closely related definitions (Devaney, 1987) from various other fields. For instance, "stochastic behaviour occurring in a deterministic system." (Berry, Percival & Weiss, 1987); "order without predictability" (Cartwright, 1991); "qualitative study of unstable aperiodic behaviour in deterministic nonlinear dynamical systems" (Kellert, 1993). Edward Lorenz would stretch the definition of chaos to include phenomena that are slightly random, provided that their much greater apparent randomness is not a by-product of their slight true randomness. In other words, real-world processes that appear to be behaving randomly, perhaps the falling leaf or the flapping flag, should be allowed to qualify as chaos, as long as they would continue to appear random if any true randomness could somehow be eliminated.

According to the author, the most currently complete definition of chaos, which is used in this research, comes from Kaplan & Glass (Kaplan & Glass, 1995: 5) where,

> "*Chaos can be defined as aperiodic, bounded dynamics in a deterministic system with sensitivity dependence on initial conditions and has structure in phase space.*"

All the above terms are thoroughly described below.

4.5 Elements of Chaos

According to the above definition of chaos there are five main attributes of chaos: there is no repetition of the same state twice; the state always stays within a finite range; the system is deterministic; it depends on initial conditions, and it has structure in phase space.

4.5.1 Aperiodicity

In simple terms, aperiodic is the behaviour that is never repeated twice. In aperiodic behaviour, although the variables of the system remain constant, there is no completely regular repetition of values, instead there is an emergence of new patterns, for instance the water flow down the sink (Sardar, Abrams, 1998: 14). Several systems, though, tend to show an unstable aperiodic behaviour where, even the slightest irritation oscillates the system in such a way that it produces a series of measurements that appear random and thus makes prediction highly inaccurate. Such behaviour in nature can be found in the image of a crowd (Sardar & Abrams, 1998: 14).

At a mathematical level, aperiodic behaviour is common in even simple non-linear sets of equations. In order to illustrate this type of behaviour, the author selected the same logistic equation $x_{t+1} = rx_t(1-x_t)$ that has been used by Phelen (Phelan, 1995). Figure 4-1 shows the solution of the logistics equation for $r = 3.7$. According to the example the value of x lies between 0 and 1 and the system is deterministic since it is just the solution of the above equation and there is no stochastic or chance elements involved. For certain values of r the behaviour of the system changes in an aperiodic way. The output ranges over a seemingly infinite (non-repeating) range of x values. For instance, for $r<2$ the system stabilises at x=0. For $2<r<3$ the system reaches equilibrium at progressively higher and higher values of x. For $r=3$ the system reaches the bifurcation point, where the steady state of x changes periodically between two values. Finally, for $r=3.7$ the system, becomes chaotic. Figure 4-2 and Figure 4-3 illustrate the above example via the bifurcation diagram.

To sum up, the aperiodicity is non-periodic (seemingly stochastic) behaviour (Abarbanel, 1996), which shows irregular oscillations that do not grow exponentially, decay, or move to a steady state (Kaplan & Gloss, 1995: 111). On the other hand, periodic systems return to the same initial state, passing through the same sequence of intermediate states over fixed intervals of time.

4.5.2 Deterministic Systems & Deterministic Chaos

A system can be defined as deterministic when it is governed by definite rules - no stochastic or chance elements are involved - that allow the prediction of the future by knowing the past and present (Thomson & Steward, 1986: 188; Wilding, 1998: 109). In other words, it behaves in a fully predictable, stable, and completely knowable way (Sardar, Abrahms, 1998).

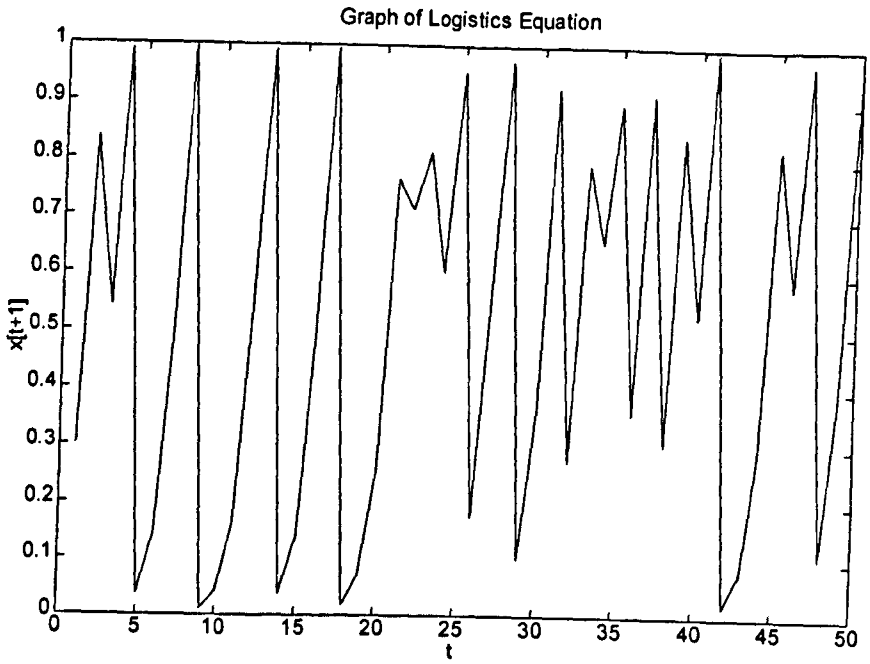

Figure 4-1: **Plot of the Logistics Equation r = 3.99, x(1) = 0.3**

Tsoukas adds that such systems can be mathematically derived from their initial conditions (Tsoukas, 1998). In the example given in Section 4.4.1, it means that for every value of x_t there is a unique value x_{t+1} which the rule or function assigns to it.

Unfortunately, most of the systems in nature are non-linear, composed from a large number of components, are open, and behave chaotically (Lowson, King & Hanter, 1999: 68). As a result, long-term prediction becomes an issue for these systems. One would argue that this comes in conflict with the above statement that determinism exists. What happens is that despite the fact that the system is deterministic the possible events that may take place are so many that current mathematical and computing abilities cannot capture this complexity.

In other words, a deterministic system is one that is governed by certain rules that are fully known and predictable and "deterministic chaos is a steady-state, evolutionary behaviour that can occur in non-linear, dissipative, feedback systems. It is characterised by self-sustained oscillations whose period and amplitude are nonrepetitive and unpredictable, yet generated by a system devoid of randomness" (Radzicki, 1990).

4.5.3 Bounded Behaviour

A system is bounded when it retains presence within a finite range and does not tend towards infinity with time (Kaplan & Glass, 1995). Again using the same example as in the above sections, the logistics function is a parabola with intercepts at x =0 and 1. If the initial condition x_0 lies in the range $0<x_0<1$, then all future iterates will also be in this range because the minimum value of $rx_t(1-x_t)$ is 0 and the maximum value is 1 (Figure 4-2 & Figure 4-3).

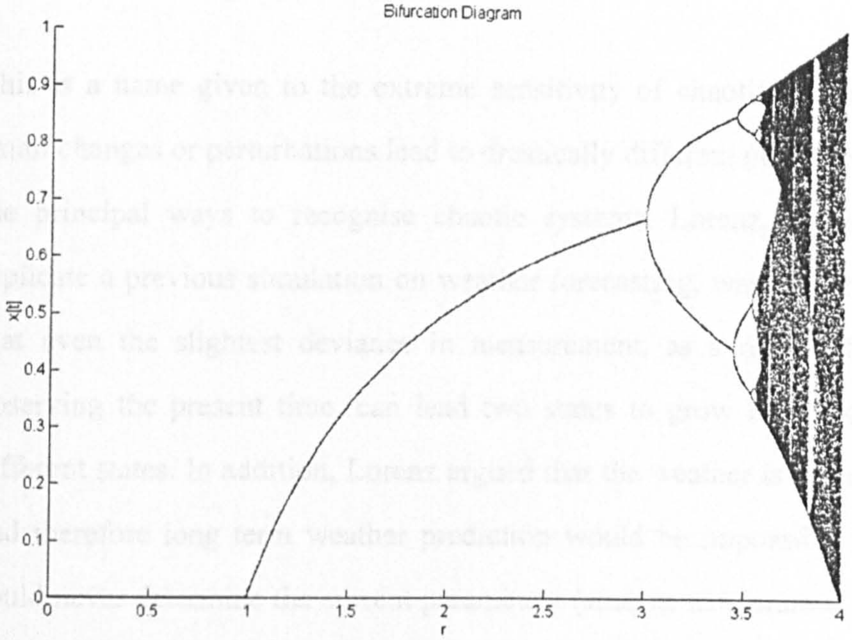

Figure 4-2: **Bifurcation Diagram**

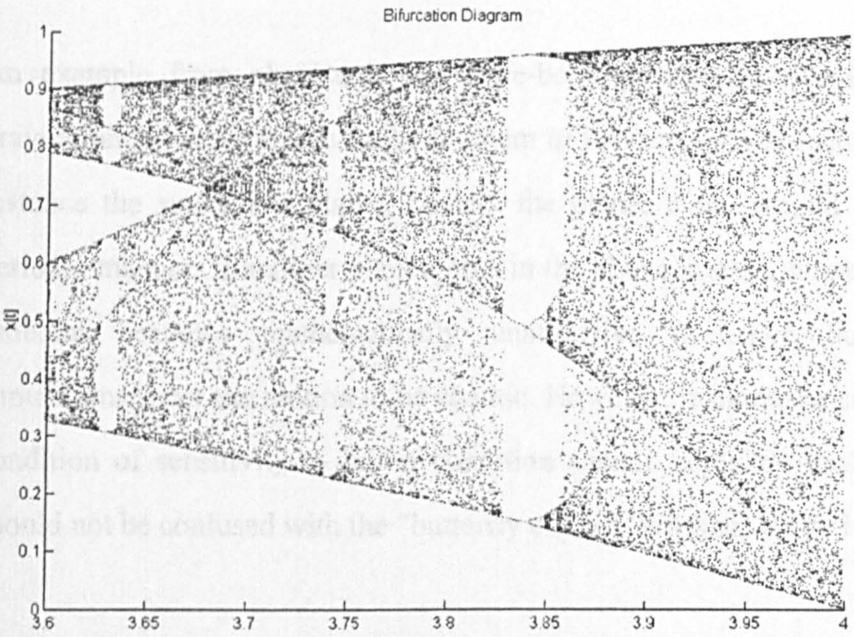

Figure 4-3: **Zoom in Bifurcation Diagram**

4.5.4 Sensitivity to Initial Conditions

This is a name given to the extreme sensitivity of chaotic systems, in which small changes or perturbations lead to drastically different outcomes. It is one of the principal ways to recognise chaotic systems. Lorenz, in his attempt to replicate a previous simulation on weather forecasting, was the first to observe that even the slightest deviance in measurement, as a result of an error in observing the present time, can lead two states to grow into two completely different states. In addition, Lorenz argued that the weather is a chaotic system, and therefore long term weather prediction would be impossible because one could never determine the current parameters (such as temperature, speed of the wind etc.) accurately enough. This implies that "an acceptable prediction of an instantaneous state in the distant future may well be impossible" (Lorenz, 1963: 133).

An example from physics is the three-body problem. Newton's theory of gravitation gives a solution to the problem of two mutually attracted bodies, for instance the sun and a planet, namely the planet move around the sun in a periodic manner. If another planet joins in the above system, however, then the problem becomes mathematically unattractive to solve but computer simulations show the motion to be chaotic. However, it should be stated that the condition of sensitivity to initial condition cannot imply by itself chaos and should not be confused with the "butterfly effect" (Wilding, 1998: 111).

Using again the same example as in the above sections, an illustration of this phenomenon is shown in Figure 4-4. The graph shows that even simple equations, such as the logistics equation, can start with almost the same initial conditions but after some time can start to deviate from each other significantly.

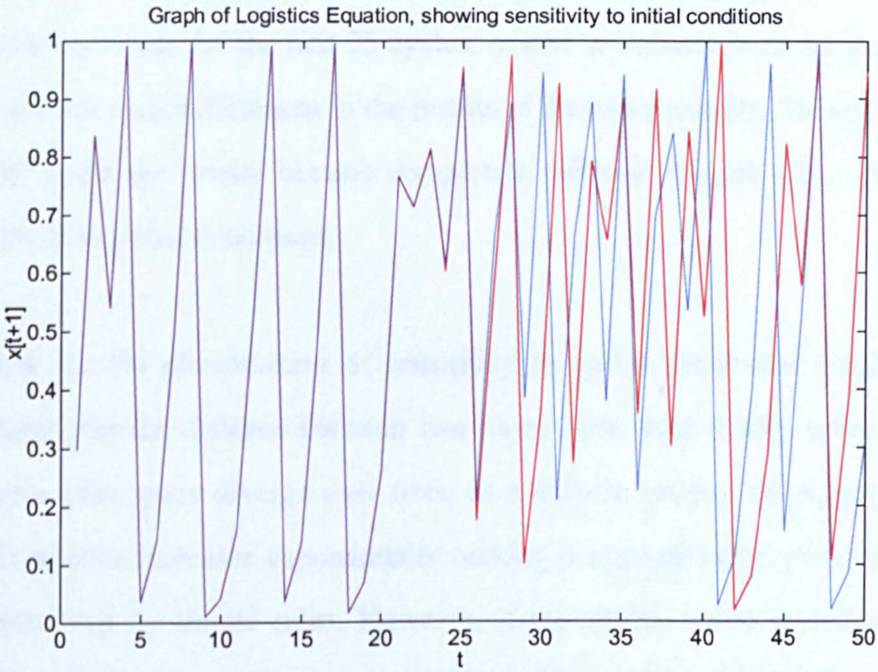

Figure 4-4: **Plot showing the Sensitivity to Initial Conditions ($r = 3.99$, $x_1(1) = 0.3$ (red), $x_2(1) = 0.30000001$(blue))**

The diagram shows that similar initial conditions can result in different future behaviours.

Figure 4-5 and Figure 4-6 also illustrate the characteristic of sensitivity to initial conditions by plotting the results of the logistics equation for x equal to 0.3 and 0.30000001. Figure 4-5 illustrates the correlation of the results of the above two logistics equations for the first 25 cycles. In can be noticed from the graph that there are not main differences in the results of the two equations. However, after the 26th cycle the results became completely different (Figure 4-6), indicating sensitivity to initial conditions.

To sum up, the phenomenon of sensitivity to initial conditions supports the statement that the distance between two trajectories from nearby points in the system's state space diverge over time. In a chaotic system, the magnitude of the divergence increases exponentially making it unpredictable, even though it is determined by simple rules. However, if the current value and state could have been known precisely then prediction could have been achievable.

4.5.5 Phase Space

A phase space represents the state of a system in a multi-dimensional plane. It is a hypothetical space having as many dimensions as the number of variables needed to specify the state of a given dynamical system. The co-ordinates of a point in phase space are a set of simultaneous values of the variables. A point in the space describes the state of a dynamical system at a particular time. All the points in the space describe the evolution of the system.

An illustration of the phase space is shown in Figure 4-7. Even by just looking at the figure we can observe a structure or correlation between past and current values, which is not obvious in a plain graph of $x(t)$ as a function t as shown in Figure 4-1.

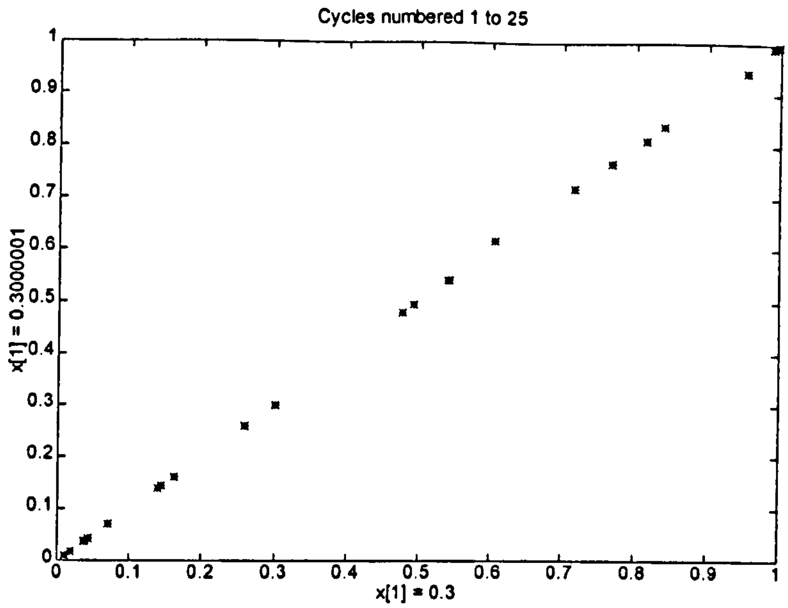

Figure 4-5: **Another plot used to show the Sensitivity to Initial Conditions. These figures plot x(t+1) with $x_2(1) = 0.30000001$ against x(t+1) with $x_1(1) = 0.3$.**

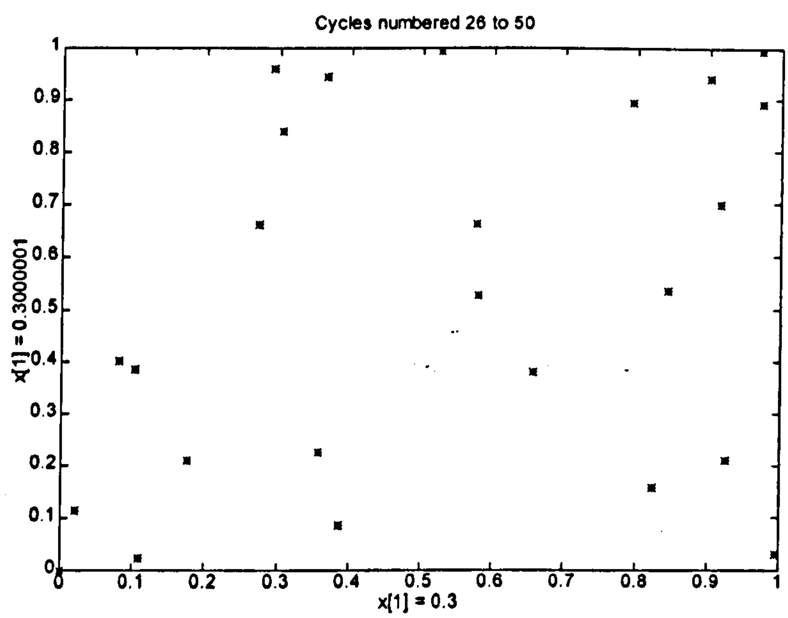

Figure 4-6: **Another plot used to show the Sensitivity to Initial Conditions. These figures plot x(t+1) with $x_2(1) = 0.30000001$ against x(t+1) with $x_1(1) = 0.3$. Figure 4-6 shows the relationship for t = 26 to 50.**

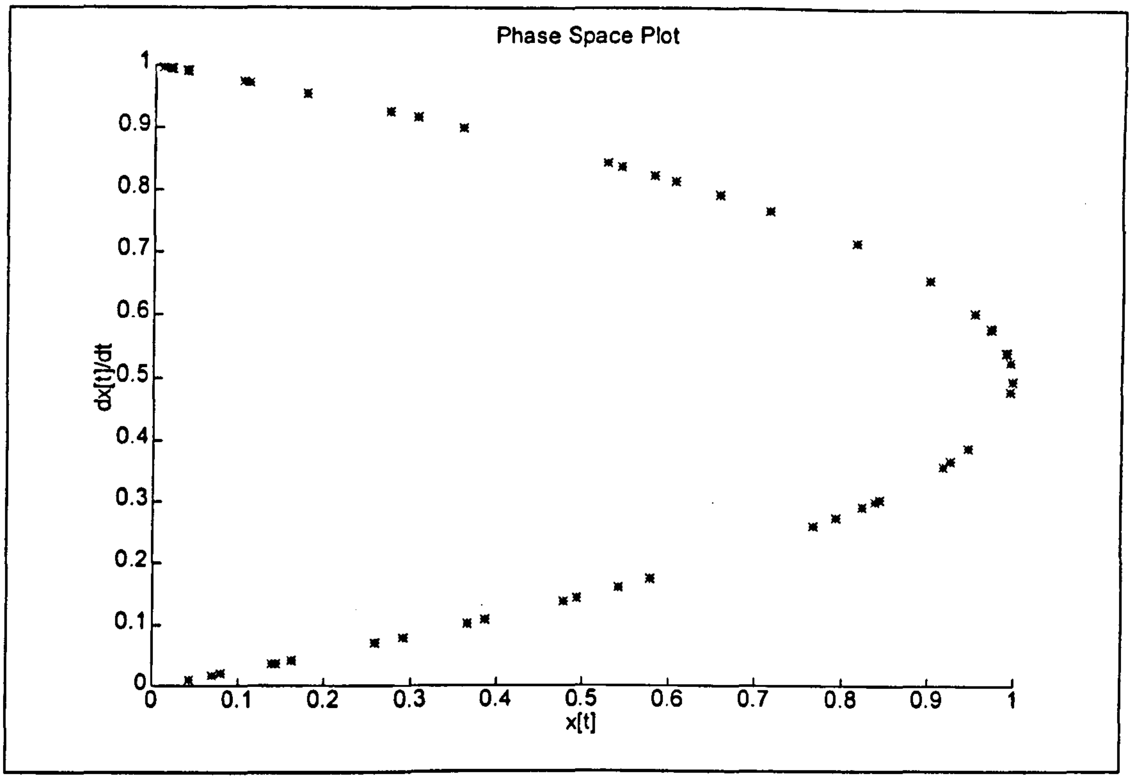

Figure 4-7: **Phase Space Plot of Logistics Equation. r = 3.99, x(1) = 0.3**

To sum up, the phase space provides the knowledge about the dynamical system at any point of time in such a way that it is easy to visualise and grasp the overview of the system's behaviour over time. In the problem to be studied in detail in Chapter 7 it is found that phase space plots reveal important information about a real system.

4.6 Causes of Scientific Chaos

One of the characterisation of chaos is "orderly disorder." This characterisation of chaos is especially interesting as it implies the main concept of chaos; order implies determinism and disorder implies unpredictability of the end result. The transition to chaos starts from a system being not chaotic to being chaotic. "There is a discernibly precise moment, with corresponding behaviour, which is neither chaotic nor non-chaotic, at which this transition occurs" (Peitegen, Jürgens & Saupe, 1992: 6). Stacey states,

> *Scientific chaos is an explanation of why most of the phenomena we observe in nature and in human behaviour have characteristics of order and stability on the one hand, accompanied by disorder and irregularity on the other. It is about the source and nature of the combined patterns of uniformity and variety in the behaviour of systems as far apart as the human heart and the market for oil* (Stacey, 1991:153).

The important question is what are the actual causes of chaos. From a mathematical point of view a necessary condition is that any set of equations describing a system must be non-linear. Examples of non-linear systems are those with feedback loops, or those which self-organise. Two important concepts following those examples are the measure of entropy and the issue of randomness.

4.6.1 Feedback Loops

Feedback is nothing else other than the process of trading information, elements, and energy from one system point to another. It is the characteristic of any system that its output affects the input of the system (Sardar & Abrams, 1998: 20). Non-linear feedback loops tend to preserve the system in a semi-stable configuration" (Young, 1994). More specifically, negative feedback tends to return the system to the equilibrium that was present before its intervention. Negative feedback work as a thermostat that "takes corrective action to discourage a deviation and preserve a steady state" (Murphy, 1996). Risk aversion could be connected with negative feedback, as humans tend not to deviate from the "normal" or equilibrium. On the other hand, positive feedback tends to push the system away from the equilibrium. Amplification could be synonymous to positive feedback. The way positive feedback works is that it drives to keep the system away from the equilibrium. Positive feedback is what magnifies small incidents to have big effects. In other words, positive feedback "amplifies deviations, working to destabilise existing states and introduce new patterns" (Murphy, 1996).

Olson states,

> *When the feedback is applied in a self-correcting way, the system displays some stability and order…when feedback is applied in other ways, the system displays little stability or order…the difference between positive and negative feedback usually is the result of very minor changes in simple controls. It's not a difference in kind; it's a difference in degree* (Olson, 1993: 2).

Positive feedback systems, from a theoretical point of view can have multiple possible equilibria. Equilibrium is an end state to which a system can evolve and in which it then remains unless something happens that disturbs the equilibrium. We make the distinction between stable and unstable equilibria (also called fixed points). The equilibrium is said to be stable if a small perturbation does not cause the system to leave the equilibrium state. It is unstable if this small perturbation causes the system to go into a different state. In positive feedback systems the possibility is that a number of different equilibrium states exist. It is then impossible to predict to which equilibrium the system will evolve. This is due to the fact that small, and apparently insignificant random events may push the system to a particular fixed point. Finally, the feedback mechanism gives some special properties to systems. These are the property of autopoiesis, interconnectedness and co-operation, and decision.

Autopoiesis

The self-renewal property of feedback grants systems some unique characteristics that are included in the concept of autopoiesis (Briggs & Peat, 1990: 153). Maturana (1981) defines autopoietic systems as "unities as networks of production of components that (1) recursively, through their interactions, generate and realise the network that produces them; and (2) constitute in the space in which they exist, the boundaries of this network as components that participate in the realisation of the network...a living system is an autopoietic system in physical space." The main attribute of a system with autopoiesis is that it has memory and the change follows the change of the broader system that they are in. However, autopoietic structures have boundaries that are transparent to the *outer world* in order to allow the trading of information, elements, and energy. Considering the number of different feedback mechanisms that a system has, the complexity of the system increases dramatically. "Our individuality is decidedly part of a collective moment. That movement has feedback at its roots" (Briggs & Peat, 1990: 154). Luhman (1987) relates the autopoietic system's dynamics to the way the socially meaningful behaviour arises. According to him "the world is overwhelmingly complex for every kind of real system...Its possibilities exceed those to which the system has the capacity to respond. A system locates itslf in a selectively constituted "environment" and will disintegrated in the case of disjunction between environment and "world"."

Interconnectedness & Co-operation

Interconnectedness and co-operation refers to the ability of systems to be associated and to communicate with neighbour systems. For open systems the trading of information and elements is vital. Therefore, interconnectedness and co-operation with other systems is essential for them. This collaboration over time may result in the interrelation of two or more systems in order to form another more advanced and complicated system. Looking back at the evolution of living systems, it is noticeable that this interconnectedness and co-operation plays a fundamental role in the development and the survival of the strongest species, in other words, competition for the fittest.

Decision

Every system has certain parameters that are held constant over a certain time. These parameters form the *rules* of the system and they determine the topology of the phase space and the presence of, for example, attractors. The set of attractors of a system moulds the basin of attraction or basin portrait of the system. A phase space depicts the evolution of a system over time. These parameters, however, are subject to change over time as a result of the system's feedback mechanisms. When the change is slow, the portrait of the system changes slowly. When the change is sudden, attractors or trajectories transform (Kauffman, 1993). This trend towards modification in the system's direction, character, or structure, is called bifurcation (Murphy, 1996).

Bifurcation is connected to the property of decision that influences the behaviour of a dynamic system (Figure 4-2). "With non-linear dynamics, this identifies the split of possible solutions after a given situation has passed the critical stage. A critical stage is connected to values of control parameters. Such parameters have a threshold at which the nature of the dynamic behaviour itself changes." (Chorafas, 1994: 24). A non-linear dynamic system, which passes a critical level, creates twice the number of possible solutions that the system had before it passed its critical level. A bifurcation cascade is often called the periodic doubling route to chaos, because the transition from an orderly system to a chaotic system often occurs when the number of possible solutions begins increasing, doubling at each increase (Figure 4-3). The most widely route to chaos involves a system undergoing a series of period-doubling bifurcations known as a Feigenbaum cascade (Grebogi, Ott & Yorke, 1987; Feigenbaum, 1983).

In other words, what happens is that when the system is close to a bifurcation point, it undertakes a qualitative change in its behaviour, in the phase portrait. This is illustrated as a transition from a steady state to a chaotic one. The system keeps on changing with different periods of oscillation until it reaches a threshold level where it shifts into the chaotic regime. In this way, causality changes after each bifurcation (Young, 1994).

4.6.2 Self-Organisation

Self-organisation is a process of evolution. The system develops new, complex structures primarily in and through the system itself. When pushed through some threshold it is able to "spontaneously generate spatial or temporal structure, and increased levels of diversity and specialisation" (Radzicki, 1990). The types of systems that can self-organise are non-linear and dissipative systems. Self-organised systems have the following attributes. The structure of the original system becomes more highly organised or structured over time (Çambel, 1993: 56). The interaction, interconnectedness, and development of their elements produce causal relationships that are highly complicated. As a result, their future structures are hard to anticipate. According to Jantsch:

> *Self-organisation is the dynamical principle underlying the emergence of a rich world of forms manifest in biological, ecological, social and cultural structures. But self-organisation does not only start with what we usually call life. It characterises one of the two basic classes of structures, which may be distinguished in physical reality, namely, the dissipative structures which are fundamentally different from the equilibrium structures. Thus self-organisation dynamics becomes the link between the realms of the animate and the animate (Jantsch, 1980: 230).*

4.6.3 Entropy

The concept of entropy is useful in discussing some of the properties of chaotic systems. Entropy has its origins in chemistry where it is used to measure the level of disorder in the system. Clausius named the measurement of the transformability of heat as *Verwandlungsinhalt,* which he later renamed as entropy coming from the two Greek words meaning "turning into". Yet, lately entropy has started to attract the attention of management as a tool to measure complexity. Shannon was the first to introduce in 1948 the concept, measuring the quality of information by means of entropy. His work was the first attempt at a mathematical theory of information or general theory of communication (Shannon, 1948). Much later, Dretske commented on his work that, "it deals with amounts of information, not, except indirectly and by implication, with the information that comes in those amounts" (Dretske, 1999: viii).

Entropy provides four main observations about the function of systems; disorder augmentation, time irreversibility, disorder for survival, and new emerged structures.

Disorder augmentation. Entropy is a measure of the randomness in a system. For example we expect that there is an increase in entropy with increasing the size of orders or the size of customers that order. Santley, Angrist & Helper, stated that, "the disorder arises because we do not know which state the system is in. Disorder is then essentially the same things as ignorance, which is how it is related to information theory" (Santley, Angrist, Hepler, 1967: 130). This implies that among other things, the prediction error increases and planning becomes more difficult, when size increase.

Time irreversibility. According to Newtonian physics, time reversibility was never an issue. This would imply that the direction of the working process of a machine is irrelevant, and time has no effect on the process. In contradiction, the second law of thermodynamics showed that the direction of time is more relevant. Assuming the case of a closed or isolated system, for instance a machine, its entropy will always increase since more of its energy is being dissipated in the heat of friction. As the machine works, the entropy increases and when it runs out of energy there is no way to turn time back to regain the energy. In the case of an open system both the external and internal processes are responsible for the increase in entropy. In any case, time can only run one way.

Disorder for survival. Notwithstanding time irreversibility and disorder augmentation, the increase of entropy is vital for the survival of a system. According to Prigogine, time could only appear with randomness. "Only when a system behaves in a sufficiently random way may the difference between past and future, and therefore irreversibility, enter its description" (Sardar & Abrams, 1998: 72).

New emerged structures. The disorder in a system increases over time, while the information provided for future behaviour decreases. During this time new variables and structures are emerging. This links to the "be" and "becoming" of Prigogine (Prigogine, 1980). "The connecting link among different forms of the entropy is that, one way or another, they are indicative of deviation from equilibrium and chaotic behaviour...entropy is inextricably linked to energy, information, and chaos" (Çambel, 1993: 129, 131).

4.6.4 Randomness

Chaos has been confused with randomness many times. Randomness is the opposite of determinism. Randomness means lawlessness and irregularity, governed by chance. A chaotic system may look random but when analysed in the right way will show that it evolves in a purely deterministic manner. Of course it may be difficult in practice to find the right way. A significant part of the data analysis given in Chapter 6 & 7 is in fact devoted to trying to distinguish between random and chaotic behaviour. At higher level of complexity a chaotic system may itself be subjected to random perturbations, either directly driven by item or such that the parameters describing the chaotic system are fluctuating. If these fluctuations are relatively small then it is reasonable to try to identify the purely chaotic part. Otherwise it makes little sense to try to separate these effects.

4.7 Issues Raised for Chaotic Systems

Chaotic systems are those that show signs of chaotic behaviour. According, therefore, to the definition of chaos (Kaplan & Glass, 1995:5), the behaviour of chaotic systems should show signs of aperiodic, bounded and deterministic behaviour, be sensitive to initial conditions, and have structure in the phase space. There are five main characteristics of chaotic systems. First the irrepeatability and irreversibility; sensitivity to initial conditions; allowing short-term prediction but not long-term prediction; qualitative changes, brought about by quantitative, a small change in some control value, and; production of fractal patterns. However, it should be emphasised that signs of the above behaviour do not directly imply chaos. They are indicators rather than criteria. The criteria for chaos are discussed further in the methodology chapter.

Non-Repetition & Irreversibility

One of the attributes of chaos is that the state never repeats itself and its state is time irreversible. Chaotic systems are open systems. Therefore they are trading energy, elements or information with other systems. Whenever an action is taking place it has some energy going towards the action and some energy lost that failed to be used for the intended action. This energy cannot be traced back as it is lost. For instance, a car does not produce work for all the petrol that it consumes as some of the petrol goes into overcoming friction.

Prediction

"The future is traditionally thought of as an extension of the past. If one knowns the starting point, one can predict the future path of an event by following a straight line" (Wah, 1998). That would have been the linear approach to things. However as was mentioned above a small random event acting on a chaotic system can have tremendous effects on the predictability of the system. Therefore, short-term prediction might be acceptable but long-term prediction may be an illusion. What we mean by this is that prediction will always be about approximation rather than accuracy. Accuracy decreases exponentially over time. Accuracy works in an inverse relationship with uncertainty.

4.8 Direct Applications of Chaos Theory to Management

The emergence of the direct application of chaos theory is becoming more and more evident (Daneke, 1997; von Rönik, 1997; Connelly, 1996). Wilding has classified the use of chaos in management into four categories of disorder: metaphoric, deterministic metaphoric, deterministic qualitative and deterministic quantitative (Wilding, 1997). The deterministic quantitative category refers to the direct application of chaos theory to management and it is the type of research that this study is classified under.

Current research related to the direct application of chaos theory is mainly coming from the field of finance management and can be further categorised according to the type of data that is used. The type of data can be either simulated or empirical. In the studies using simulated data Moritz investigates the presence of chaos in the German stock market by using neural nets data and looking at the Lyapunov exponent (Moritz, 2000). Wilding has used simulated data to investigated signs of chaotic behaviour in the warehouse supply chains using a series of chaos theory tests (Wilding, 1998). Similarly, Hibbert et al looked at market competition dynamics for chaotic behaviour using artificial data (Hibbert, Jiang & Wilkinson, 1998)

In studies using empirical data, Kiel looked at the phase plots of each employee's per minute labour cost data to investigate the work effort performance (Kiel, 1993). Blank, on the other hand, calculated the Lyapunov exponent and correlation dimension of future price data in order to investigate the presence of chaos in future markets (Blank, 1991).

Other studies used both simulated and empirical data in order to compare the results. Koput investigated the structure of attention and ideas in active research given by simulated and real data by looking at the correlation dimension and the entropy measures (Koput, 1997). Finally, Hsieh explored the presence of chaos in the financial market by using the method of correlation dimension (Hsieh, 1991).

4.9 Summary

The purpose of this chapter was to describe the main concepts of chaos theory and its applications to social sciences and management. It was shown that chaos theory is the invention of not one but several academics working in related fields including Lorenz (1963), Feigenbaum (1983), and the Santa Cruz Dynamical Systems Collective (Gleick, 1987). Importantly "... unless the starting can be specified with infinite precision, chaotic systems quickly become unpredictable. Chaotic systems thus combine qualities that traditional science considered non-ethical and that quantum mechanics did not anticipate. Chaotic systems are both deterministic and unpredictable (Hayles, 1990)."

In other words, chaos "implies a kind of inherent "uncertainty principle" - not just in how we perceive the world but in how the world actually works." (Cartwright, 1991: 45). "We may fully understand the rules that govern behaviour at the individual or "local" level, but the global result is nonetheless impossible to predict beyond anything but the immediate future" (Cartwright, 1991). The forecasting problem is inherent rather than situational. "While the prediction of chaotic behaviour may be impossible, understanding the order that gives rise to it may not be as difficult as we thought. Highly complex and unpredictable behaviour, in other words, can be the product of quite simple and accessible rules." (Cartwright, 1991: 45).

PART III

RESEARCH METHODOLOGY

Chapter 5:

RESEARCH METHODOLOGY

& DATA COLLECTION

Chapter 6:

DATA ANALYSIS

Chapter 5

Research Design & Data Collection

Chapter 5:

Research Design & Data Collection

This chapter provides an overview of the research process, research design and data collection methods. The overview begins with a general description of the main stages of the research process of the thesis. It then proceeds to a detailed description of the research design and criteria for selecting the specific research methodology. In sequence, the data collection section identifies and discusses the variable, type of data, data collection methods, and preparation of the data. Finally, the chapter summarises the main limitations of the proposed research design and methodology.

5.1 Introduction

The purpose of this thesis is to develop a methodology for chaotic analysis to detect, analyse and anticipate high-level variability in logistics demand (Chapter 1). Inability to effectively handle such oscillations can have severe impact on the effective planning and control of logistics management inventory, as well on total logistics costs (Chapter 2 & Chapter 3). Current approaches focus on identifying the nature of high-level fluctuations and propose intervention strategies to manage them. Yet, none of these approaches has examined the possibility of deterministic or chaotic fluctuations (Chapter 3). Therefore, potential benefits from the direct application of chaos theory have never been explored (Chapter 4). The purpose of this chapter is to explain and defend the procedures followed in this research; in a way that enough information is provided for another researcher to be able to replicate this study (Yin, 1989).

5.2 Research Process

The research process is the sequence of stages of actions necessary to complete an investigation. Zikmund recognises seven stages in research process. These are defining the problem, planning the research design, planning the sample, gathering the data, processing and analysing the data, formulating conclusions and preparing report, and finally redefining the problem (Zikmund, 2000: 54). Sekaran, on the other hand is more "detailed", distinguishing eleven main stages in research process (Sekaran, 2000: 90). Those are observation, preliminary data gathering, problem definition, theoretical framework, and generation of hypothesis, scientific research design, data collection analysis, and interpretation, deduction, report writing, report presentation and finally managerial decision-making. The research process of this study is a combination of both the above approaches (Figure 5-1).

Thus, the stages of the research process of this thesis are: literature review, problem definition, theoretical framework, research design, data collection, data analysis, data interpretation, and thesis writing. The research problem was defined based on an extensive literature review first on third party logistics, demand variability and chaos theory. The literature review on logistics revealed that high-level variability impact on the efficiency of the third party logistics operations (Chapter 2).

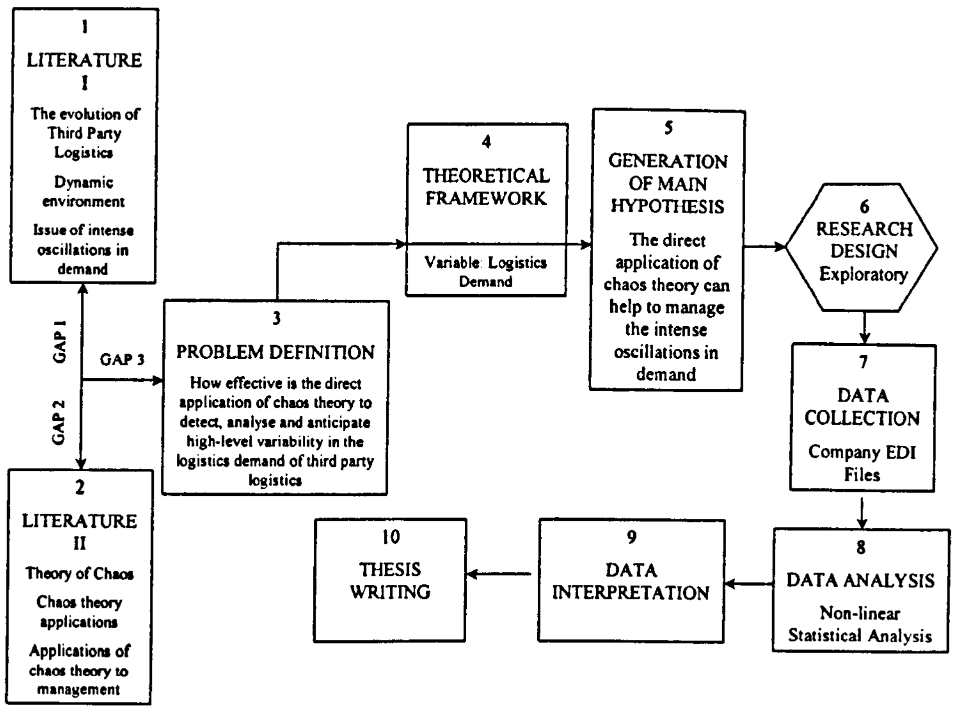

Figure 5-1: **The Research Process of the Thesis**

Adapted from: Sekaran, U. (2000) *Research Methods for Business: A Skill Building Approach,* John Wiley & Sons, Inc.

Current approaches to analyse and anticipate high-level variability have been unsuccessful. Yet, the direct application of chaos theory has not been yet explored to investigate the specific issue (Chapter 3). Chaos theory, however, is a good candidate to assist in solving the issue of high variability in logistics demand (Chapter 4). As a result the research question of this thesis was defined based on the above arguments (Chapter 1). Having determined the research issue the next step is to define the research design of the study.

5.3 Research Design

A research design is nothing other than a framework for conducting the research. Its purpose is to lay the foundation for conducting the research project (Naresh, 1996: 86). It consists of the specification of procedures for collecting and analysing data necessary to facilitate the research (Kinnear & Taylor, 1991). Research design is necessary to ensure that the study will (1) be relevant to the research problem and (2) use economical procedures (Churchill, 1999). Therefore, in order to determine the type of research design it is necessary to have a clear understanding of the nature of the problem that is to be investigated (Zikmund, 2000:53)."In terms of the fundamental objective of the investigation, research designs can be classified into three types: exploratory, descriptive, and causal (Selltiz, Wrightman and Cook, 1976).

As was discussed in the previous section, the nature of enquiry requires an exploratory research design (Figure 5-2). Exploratory research is appropriate in four cases. Those are when it is needed to gain background information, define terms, clarify problems and hypothesis, and establish research priorities (Burns & Bush, 2000; 131). The reasons for adopting an exploratory design in this research are three; to gain insights, clarify problems and establish research priorities. More specifically, new insights will be gained on the applicability of the direct application of chaos theory to explore the nature of intense oscillations and assist in their control. The identification of signs of chaotic behaviour in demand will help to clarify the source of high oscillations and therefore to identify ways to control them. Finally, the combination of new knowledge and clarification of the issues will open new avenues of research direction.

There are five different ways in conducting an exploratory research. These are secondary data analysis, experience surveys, case study analysis, focus groups and projective techniques (Burns & Bush, 2000:132-133). The method selected to execute this research is case study analysis.

5.4 Research Method: Case Study

Despite the fact that the majority of logistics research is based on quantitative research approaches (Ellram, Kwolek, LaLonde, Siferd, Pohlen, Walker, and Wood, 1994), case study analysis has drawn the attention of business research (Mentzer & Kahn, 1993). The main reasons that contribute to the increase in interest in using case study as a methodology in logistics research are three. First, it can detect and look at relationships that would not otherwise be noticed with quantitative methods and provide depth and insight into a little known phenomenon (Ellram, 1996). In that way, the case study analysis can, secondly, provide an understanding of complex interactive activity contributing to the development of new theoretical systems and statements (Eisenhardt, 1989). Finally, a case study design can be combined with quantitative analysis if further understanding is needed to enhance further insights.

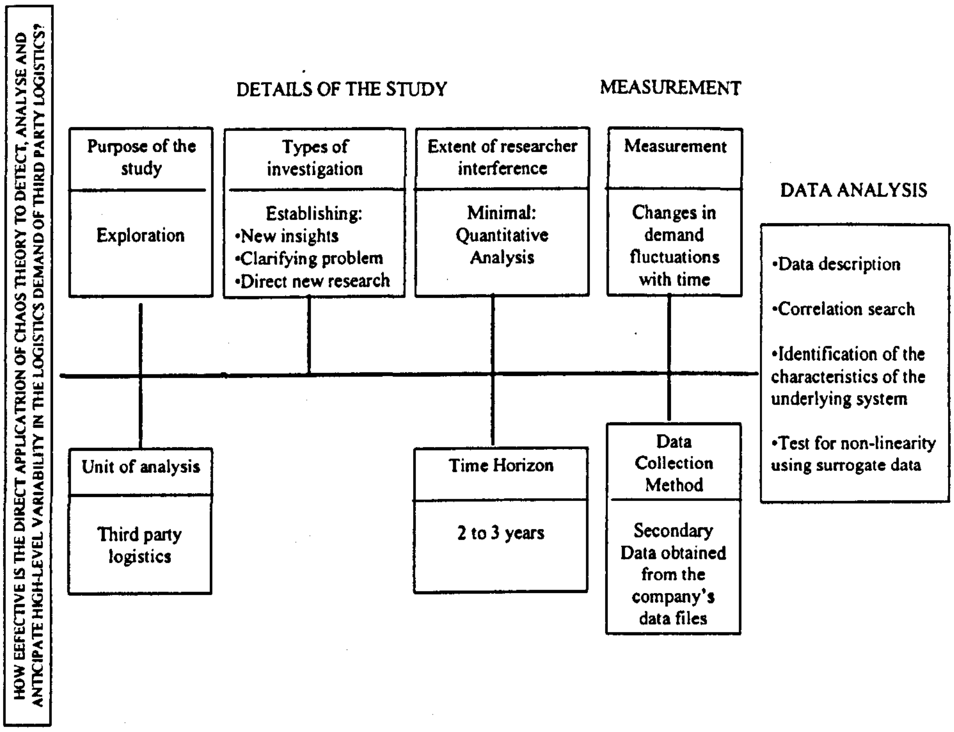

Figure 5-2: **Research Design of the Thesis**

Adapted from: Sekaran, U. (2000) *Research Methods for Business: A Skill Building Approach,* John Wiley & Sons, Inc.

Nevertheless, there are several misconceptions of using a case study as the method of analysis. Ellram summarises them as:

> *(1) case study research and teaching are closely related (2) the case study method is only a qualitative research tool (3) the case study method is an exploratory tool that is appropriate only for the exploratory phase of investigation (3) each case study represents the equivalent of one research observation. Thus, extremely large numbers of case studies are required to produce any meaningful results (5) case studies do not use a rigorous design methodology (6) anyone can do a case study; it's just an ad hoc method (7) results based on the case study methodology are not generalizable* (Ellram, 1996).

These misconceptions lead to concerns on the internal validity, external validity and generalisability, and reliability, discussed later in this chapter (Ellram, 1996; Seaker, Waller & Dunn, 1993). Nevertheless, case study analysis was selected as a methodology for this study. The main reason for this selection is related to the nature of this research. As was mentioned before the type of the research is exploratory. It aims to test whether the direct application of chaos theory can help to detect, analyse and/or anticipate high variability in logistics demand. In order to accomplish this the type of data analysis should be quantitative. In addition, the data gathered should have certain characteristics; i.e. be in a time series format of at least two years. Clearly, the case study design of this study is unique because of peculiarity of the data analysis (see Chapter 6).

5.4.1 Case Study Sampling

Sampling is nothing other than the procedure of selecting a part of the examined population in order to draw certain conclusions on its nature and behaviour. The main reason for sampling is that the investigation of the whole population is not feasible. Therefore, the study of a part of the population could assist in making valid generalisations for the whole population. However, the right selection of the sample is fundamental in order to make a sound generalisation. According to Zikmund (2000; 342-363), there are seven main stages in the selection of a sample (Figure 5-3).

According to those steps the population group of this research is logistics companies that experience high-level fluctuations in their demand. The sample unit selected is the demand or number of orders for distribution. The unit of demand should satisfy two main criteria. It should be in a time series, or compatible, format and at least two to three years long. These criteria are related to the prerequisites for the data analysis. Thus, one case study was selected.

The type of sampling of this case is convenient non-probabilistic. There are two main reasons for this choice, confidentiality, and availability and usefulness of the accessible data. Many companies contacted were reluctant to disclose their data.

In addition, many potential companies either did not have sufficient data or the data was not in a workable format for the purposes of this research. The main weakness of a convenient non-probabilistic sample is that generalisation to the wide population may be debatable. However, the purpose of this research is to explore the possibility that one of the reasons for unpredictable demand fluctuations could be that of deterministic chaos and therefore chaos theory could be directly applied to explain them rather than to provide a generalisation that explains a standard behaviour for the whole population.

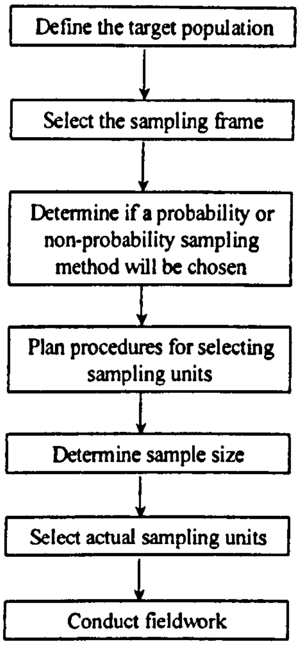

Figure 5-3: **Stages in Selection of a Sample**

Adapted from: Zikmund, W.G (2000) *Business Research Methods* (6th ed.), The Dryden Press-Harcourt, Inc.

For the appropriateness of the above sampling to the study, three main criteria applied, level of accuracy, time and advance knowledge of the population (Zikmund, 2000; 360-361). Third party logistics is a field that experiences the highest level of fluctuations in its demand (Chapter 2). Therefore, an accurate assumption can be made that it is a good sample to be examined. Furthermore, time and resources of conducting the research have played an important role in the selection of the size of the sample. Finally, it was the author's main interest to focus the research on the investigation of third party logistics.

The author looked at the third party logistics companies' profiles and made a list of potential companies. This information was gathered from reviewing academic and business periodicals, and looking at the web pages of the companies. Twenty companies were found to be relevant and were personally contacted by mail. The letter was sent to the logistics manager of the company. Only in one case was the contact with the company established directly by recommendation. Despite the fact that twenty companies were contacted only five agreed to participate in the research. From those five only one was qualified to provide sufficient data, including the one by recommendation.

5.4.2 Quality of Case Study Design

The quality of the research design involves the internal validity, external validity and generalisability, and reliability. According to Ellram internal validity is irrelevant to those researches that are exploratory or descriptive (Ellram, 1996) so it is not of a concern in this research.

The external validity establishes the level of accuracy with which the results represent the phenomenon studied. If the level of accuracy is high and the results allow for a "range" of activity, while still providing a consistent explanation (Ellram, 1996), then generalisability of the results is easier to be established (Yin, 1981). In this study, the level of accuracy of the quantitative analysis is high. Nevertheless, the generalisation of the results should be treated very cautiously. Yin comments,

> *...case studies are like experiments, are generalisable to theoretical propositions and not to populations or universes. In this sense, the case study, like the experiment, does not represent a "sample," and the investigator's goal is to expand and generalise theories (analytic generalisation) and not to enumerate frequencies (statistical generalisation)* (Yin, 1981).

5.5 Data Collection

Having identified the research design the next step is to look at the variable, and identify the type and method of accessing and collecting the data.

5.5.1 The Variable

A variable is the unit of analysis or the attribute of an entity that has been chosen to be further investigated. It can be classified as either quantitative or qualitative. The qualitative variable is a non-numerical attribute, such as gender, while the quantitative variable is a numerical attribute, such as income. Quantitative variables can be further categorised as continuous or discrete or "quantised". Discrete variables can only take one of a range of distinct values between the start and end of a scale, such as date of birth. Continuous variables can take any value between the start and end of the scale, such as height (Hussey & Hussey, 1997: 141-142). According to this description, the variable in this study is quantitative and continuous. As mentioned in previous chapters, it is the logistics demand or the size of orders requested from the customer for distribution.

The variable examined looks at the total quantity (units of orders) of orders per fixed time intervals, independent of the customer. The variable is investigated from the supplier's position (third party logistics or product supplier). A customer's or cross entities' approach was not considered for two main reasons. First, a cross section investigation would not have satisfied the purpose of this research - to investigate the nature of high levels of fluctuations in logistics demand. Likewise, a customer's approach would not have been in the interest of this study, as it would be closer to a retailing investigation. The second reason focuses on two significant limitations in investigating each customer's demand activity separately instead of the total demand activity placed on the provider. Those are the inflexible data format and large number of customers. The format of the records is not specific enough to allow an investigation by individual customer's demand activity.

5.5.2 The Type of Data

There are two types of data sources, primary and secondary (Churchill, 1999). Primary data is gathered and assembled specifically for the research at hand, while secondary data has been previously gathered for another use (Zikmund, 2000). The source that has been selected for the purpose of this research is secondary data. There are three reasons for using secondary data in the analysis; to fill a specific reference on some point, to use it as an integral part of a larger research, or to be used as base for a further research study (Cooper & Emory, 1995: 241). The reason for selecting secondary data in this research is that no other source could provide detailed records of the demand activities of the companies other than the companies themselves. The advantages of using secondary data are that it is easy, quick and cheap to be collected (Cooper &

Emory, 1995: 241). The main concern of using secondary data is the level of appropriateness of data for the purposes of the study. The data was gathered for other purposes therefore there would always be issues such as relevance of the units of measures, the "condition" of the data to the current research. Chapter 6 discusses the main limitations of using time series as a secondary data, which is the type of data that is needed for the analysis.

Time Series

In Chapter 1, it was mentioned that one of the main objectives of this research was to investigate the nature of the fluctuation in demand. In order to accomplish this we need to look at the time evolution of the variable. Thus, the type of data that can provide this information is time series. Time series supply a record of observations, each one registered at specific, equal time intervals. Time series is nothing other than "a collection of observations made sequentially in time" (Chatfield, 1996: 1). The objective of time series analysis can be summarised in three categories; description, prediction and control (Chatfield, 1996: 5-6). Description requires a plot of the data. It allows the observation of data behaviour such as possible change points in trends, fluctuations, and seasonal effects. Explanation of certain data behaviour can be obtained by using the variation of one time series to explain the variation of the other. Finally, the prediction of certain time series behaviour by use of particular forecasting tools can lead to certain control procedures.

There are three main issues raised in time series analysis. The first issue raised is related to the selection of linear or non-linear techniques in analysing the data. This is related to whether the examined observations are independent or dependent. Independent observations are those that do not rely upon the past. Therefore their prediction is not dependent on what happened in the past. On the other hand, dependent observations are those whose future behaviour relies on their past experience. In the event that the future can be fully predicted, these time series are called deterministic. Similarly, stochastic time series are those where the future is only partially determined from the past. In this case, time series analysis is difficult and special tools are required. It is often a mistake to treat stochastic data as deterministic and vice versa.

The issue is that "different time series may or may not look alike...it is important to know the background of the underlying data" (Çambel, 1993: 196) in order to treat them with appropriate tools. For instance, all chaotic time series are non-linear but not all non-linear time series are chaotic. An error in the appropriate tool selection may lead to improper description, explanation, prediction or control of the data. The next section explains the methods of time series analysis that are used in non-linear analysis, as non-linear data is the subject of this thesis.

Limitations

There are five main issues that the use of real time series data can raise. These are lack of data points, data aggregation, noise, missing values and format compatibility. In most instances, the available or accessible size of data that the firms can provide is not adequate to get valid results in the analysis. In addition, in some cases the format of data available has been aggregated or needs to be aggregated depending on the style of the data imported. Real data has another main disadvantage, noise. Noise can distort the results in such a way that it is not possible to get valid results from the analysis. Missing values is again an issue in using real time series. The data files of most companies may have lost, omitted or erased data inputs that are impossible to reveal and sometimes to identify. Finally, the format in which the data has been recorded can prove to be problematic in the analysis.

5.5.3 Data Collection Methods

Secondary data can be extracted from either internal or external sources. External sources are created outside the organisations, for instance published statistics. Internal sources come from the company. The secondary data used in this research came from internal sources. It was extracted from the computerised, on-line systems of the companies, such as Electronic Data Interchange (EDI) systems. This type of system can provide accurate information about all the orders that have been placed within the company. EDI "involves the direct, computer-to-computer transmission of inter-company transactions. Although many people think of EDI as relating to ordering transactions, EDI often involves a broader set of credit memos, shipping documents, or any other routine transactions between companies" (Johnson, Wood, Wardlow & Murphy, 1999: 539).

The advantages of using internal sources for extracting secondary data are two. First, they are reliable sources of information and second it is a fast procedure. One of the limitations however is the appropriateness of the data. The format of the data is not always suitable for direct application and a lot of preparation work may be required in separating the relevant information and bringing the data to a workable format. The next section discusses the data preparation process that was needed in this research.

5.6 Preparation of Data for Data Analysis

The preparation process of the data of this study is shown in Figure 5-4[1]. The first step for the preparation of the data is to identify the structure of the file. What kind, and in what format is the information available? The second step is to identify and evaluate this information. Can this information be used for a time series analysis? The next step is to identify the specifications of the data. How is the demand recorded? For instance, "is it input by customer or daily transaction?" Then, after separating the data to be investigated, the data has to be ordered in time. That may require an aggregation by either daily or weekly transactions. In order to do this a small computer program may be required to be written. After this stage is completed the data is ready to be analysed.

5.7 Summary

To sum up, the research design of this study is exploratory. Its purpose is to provide new insights into the way intense oscillations in demand can be moderated. The type of data is secondary and is extracted directly from the computerised data files of the companies. Three main problems were raised with data collection; confidentiality, short data sets, and inappropriate data format.

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[1]The program that has been used in this research, for the purposes of the preparation of the data of the first case study, is shown in Appendices.

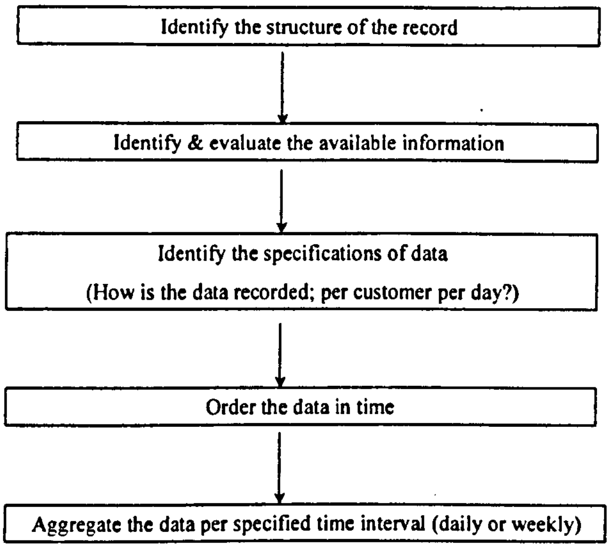


Figure 5-4: **Preparation Process of the Data**

Chapter 6

Data Analysis

Chapter 6:

Data Analysis

This chapter describes the data analysis and explains the different methods and statistical tests of the CASTS constructed to describe and analyse the data. It is divided into three main sections. The first section describes the philosophy of the underlying data analysis. The second section rationalises each method and tests the different steps followed in the data analysis of this thesis. Finally, the last section outlines the limitations and pitfalls of the proposed data analysis.

6.1 Introduction

One of the main research issues of this thesis is to investigate whether the observed high fluctuations in demand can be better modelled using a chaotic theory approach. However, the analysis of non-linear time series is not an easy task. It becomes even more complicated when the fluctuations become so intense as to raise suspicions that the underlying time series may be a good candidate for randomness or chaos. This section provides the background information of the methods and the tests followed in this study.

6.2 Philosophy of Data Analysis and CASTS

As mentioned above the analysis of time series using a non-linear approach is complicated. The philosophy of data analysis design is to provide a framework of analysis (CASTS), rather than a new method, on how to investigate data sets with high variability in short-time series and detect possible signs of chaotic behaviour. The method of CASTS is an amalgamation of linear and non-linear techniques, forming a methodology that non-chaos theorists or statisticians can follow easily in order to investigate the behaviour of complex dynamical series. The importance of CASTS is that it can provide a better understanding and interpretation of highly fluctuating time series data.

The CASTS design is divided into three main phases – description of the data, search for correlations and description of the main characteristics of the system (Figure 6-1) - and involves testing three main hypotheses (Figure 6-2). The purpose of the first phase is to provide a summary of the basic statistics describing the underlying data set. This phase is important to secure the correct import of the data. The second phase focuses on investigating the nature of the correlations between past, current and future data points. This phase is important because it tests for linear and random behaviour in the underlying time series. Having proved that the data set is non-linear the next step is to identify the type of non-linearity. The third phase of CASTS does just that. It has to be mentioned that the selection of the tests of this phase are directed towards the identification of chaotic behaviour.

As it can be seen from Figure 6-1, the method of CASTS involves two surrogate data tests at the end of Phase II and Phase III. The purpose of the surrogate data test is to increase the validity that the results obtained in Phase II and Phase III are not random or coincidental. A thorough description and explanation of CASTS phases is presented in the following sections.

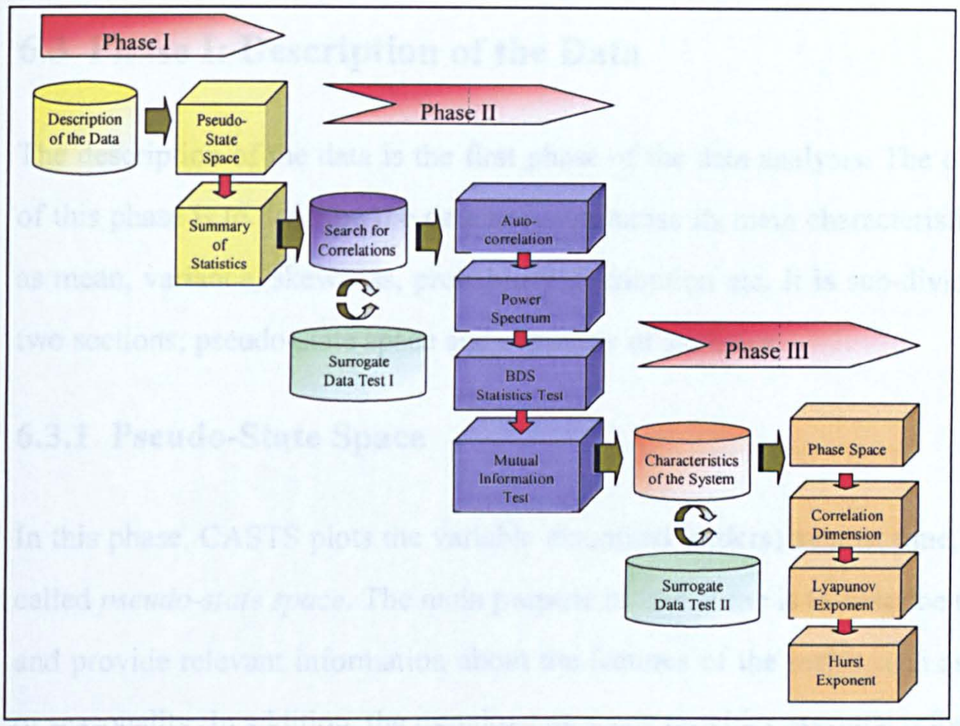


Figure 6-1:**Data Analysis Design**

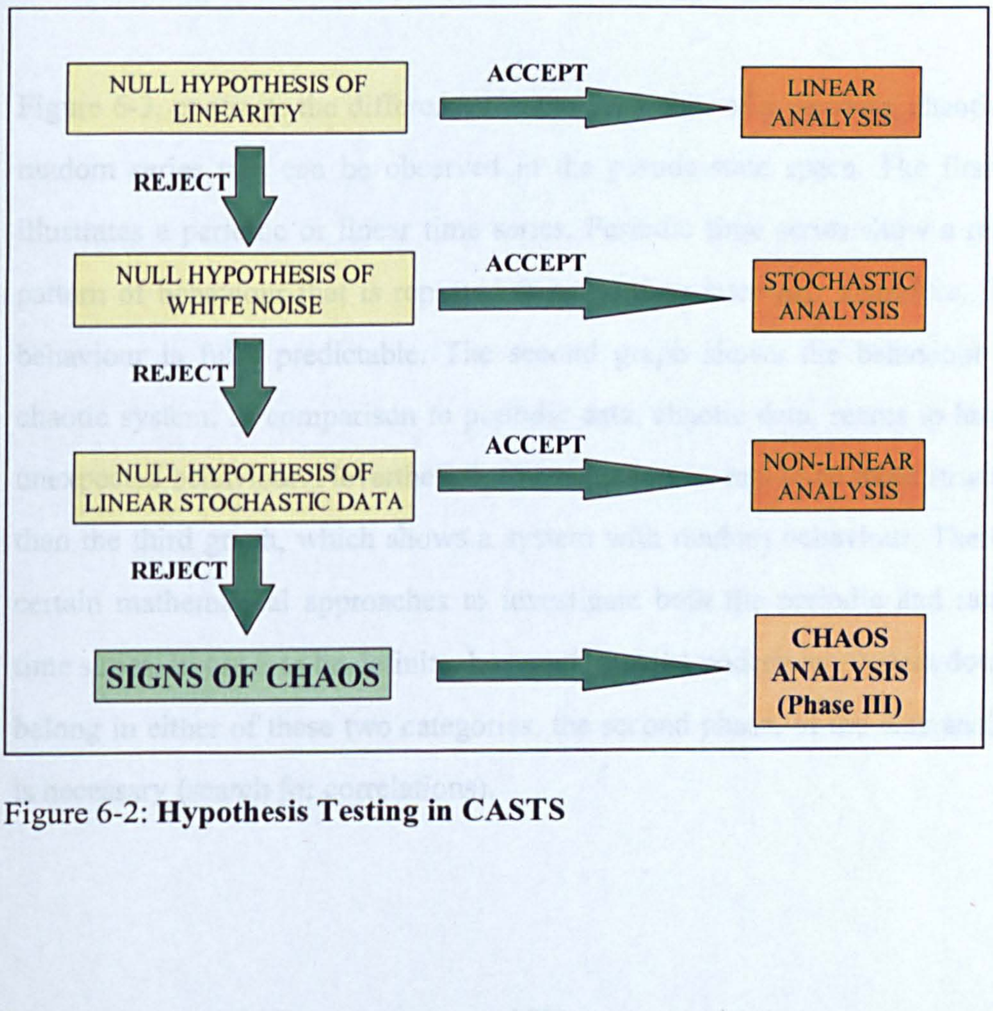


Figure 6-2: Hypothesis Testing in CASTS

6.3 Phase I: Description of the Data

The description of the data is the first phase of the data analysis. The objective of this phase is to describe the data and summarise its main characteristics such as mean, variance, skewness, probability distribution etc. It is sub-divided into two sections; pseudo-state space and summary of statistics.

6.3.1 Pseudo-State Space

In this phase, CASTS plots the variable examined (orders) against time, the so-called *pseudo-state space*. The main purpose of this phase is to describe the data and provide relevant information about the features of the series such as trends or seasonality. In addition, the pseudo-state space provides essential information as to whether the data has been recorded properly with no outliers or discontinuities that can affect further data analysis, being present.

Figure 6-3, contrasts the differences in the behaviour of a periodic, chaotic and random series that can be observed in the pseudo-state space. The first plot illustrates a periodic or linear time series. Periodic time series show a regular pattern of behaviour that is repeated at equal time intervals. Therefore, future behaviour is fully predictable. The second graph shows the behaviour of a chaotic system. In comparison to periodic data, chaotic data, seems to have an unexpected behaviour. Nevertheless, this behaviour seems to be more structured than the third graph, which shows a system with random behaviour. There are certain mathematical approaches to investigate both the periodic and random time series. In order to be definite, however, that the underlying system does not belong in either of these two categories, the second phase, of the data analysis, is necessary (search for correlations).

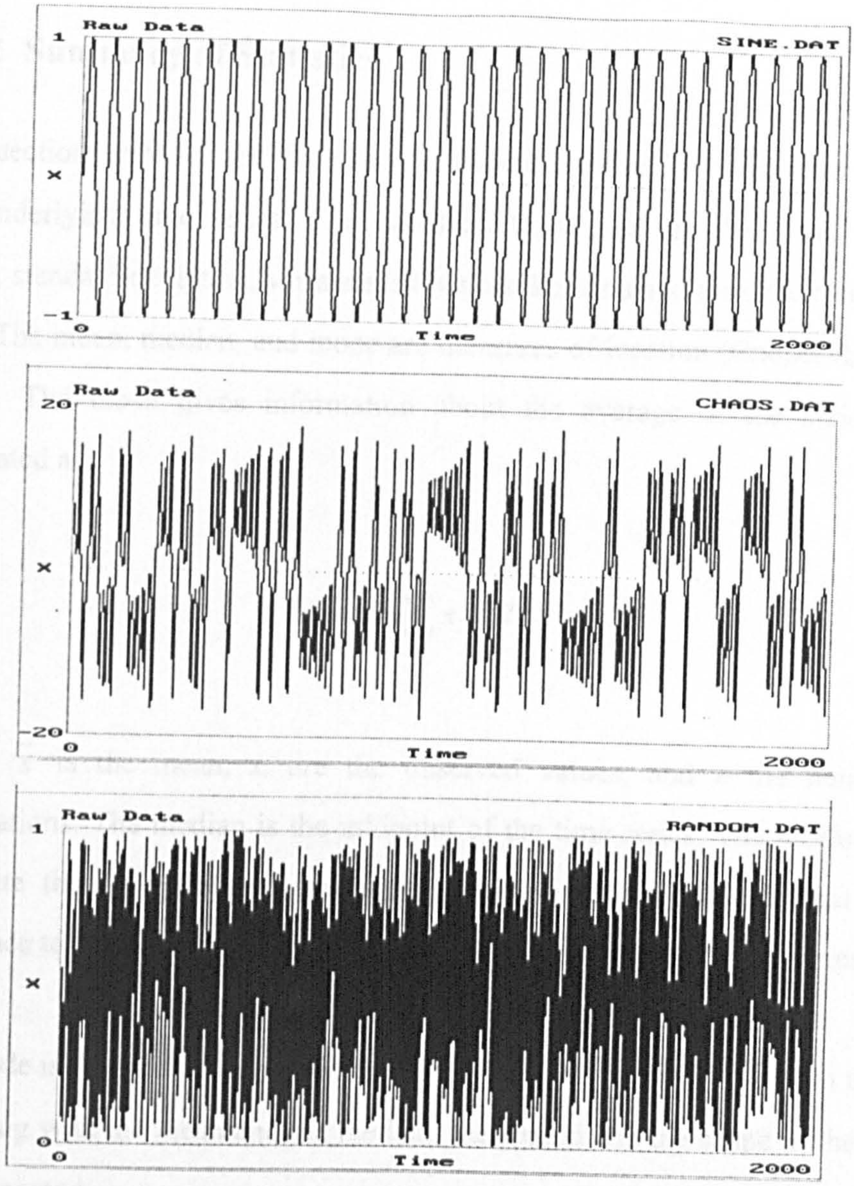


Figure 6-3: **(a) Periodic Plot (b) Chaotic Plot (c) Random Behaviour Plot**

(a) An example of periodic data is the sine wave. The plot represents the change of the sine wave via time. The main characteristic of this behaviour, as it can be noted from the graph, is that it is repeated within equal time intervals. (b) From this graph data seems to behave randomly although it is chaotic (c) This is an example of white noise.

6.3.2 Summary of Statistics

This section provides the necessary statistical information needed to describe the underlying time series. The statistical tests used are the mean, median, mode, standard deviation, variance, skewness, kurtosis and maximum-minimum data. The mean, median, and mode are measures of location (Cooper & Emery, 1995). The mean gives information about the average of the series. It is calculated as:

$$\bar{x} = \sum_{i=1}^{N} x_i \Big/ N$$

where, $\bar{x}$ is the mean, x_i are the observed values, and n the number of observations. The median is the midpoint of the time series. The median helps to locate the centre of the series and its main characteristic is that it has resistance to the extreme values. It is the average of the two middle scores.

The mode is the most common value in the series. Its importance lies on the fact that along with the mean and the median, the spread and the shape of the series can be located.

Next the variance, standard deviation and range are measures of the spread in the data. The standard deviation is equal to the square root of the variance. The variance measures deviation of the data points from the mean and the greater the variance is the greater the deviation. The variance is calculated as:

$$s^2 = \sum_{i=1}^{N} (x_i - \bar{x}) \Big/ (N-1)$$

where, s^2 is the variance. The range is the difference between the largest and the smallest value. When the range is used along with the standard deviation it can give some indication about the homogeneity or heterogeneity of the series. For heterogeneous distributions the ratio between the range and the standard deviation lies between 2 and 6 (Cooper & Emery, 1995).

The next set of the descriptive statistics is the measure of shape. Skewness measures the deviation of the series from symmetry. When the series approaches symmetrical distribution the skewness is close to zero. Otherwise, if it lies towards the small values then it is negatively skewed and if it is lies toward the large values it is positively skewed. It is calculated as:

$$sk = \frac{\sum x^3 / N}{(\sqrt{\sum x^2 / N})^3}$$

On the other hand, kurtosis measures the level of peakiness or flatness in the time series. It is calculated as:

$$ku = \frac{\sum x^4 / N}{(\sum x^2 / N)^2} - 3$$

When the data is normally distributed, the kurtosis value is almost zero. However, if the kurtosis is negative the series is platykurtic or flat and when it is positive it is leptokurtic or peaky (Cooper & Emery, 1995). It should be noted that the higher or lower the absolute value the more extreme the characteristic.

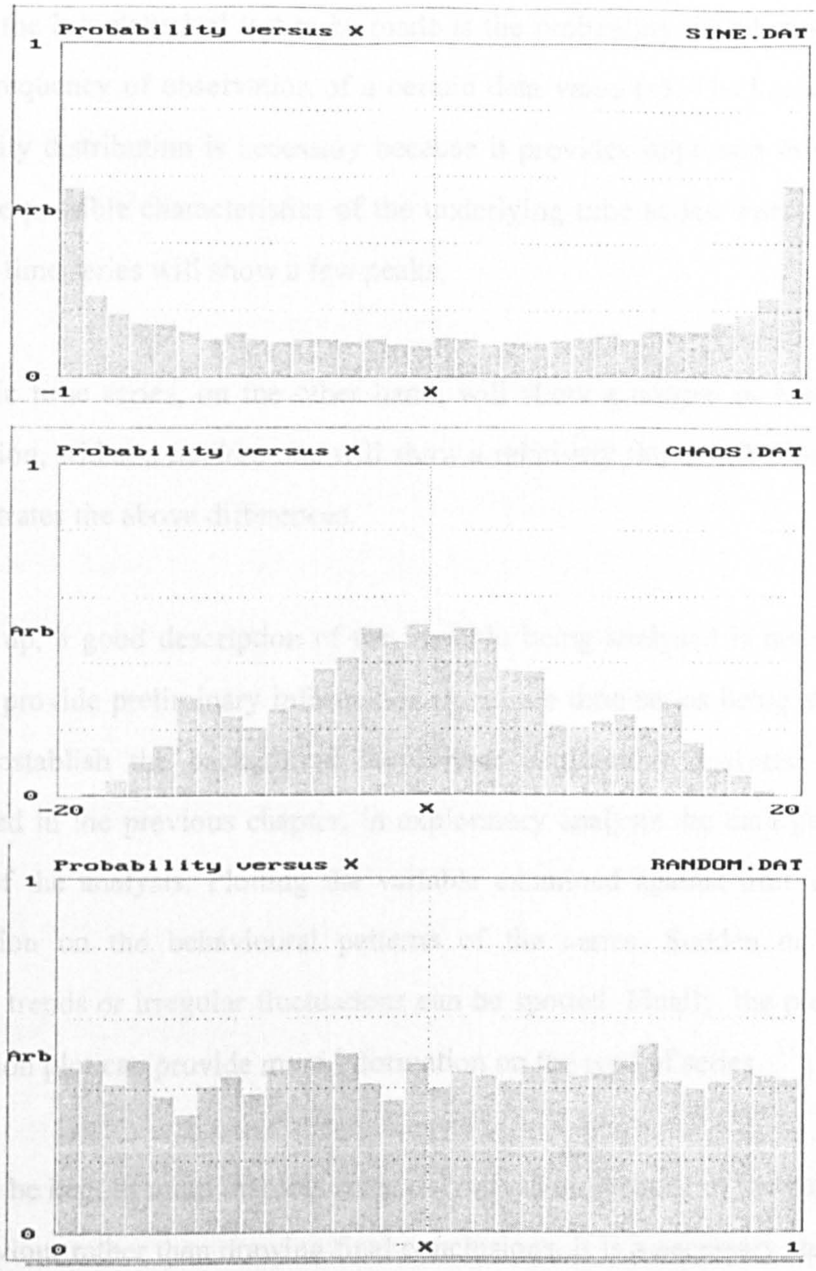


Figure 6-4: **Probability Distribution of (a) Periodic (b) Chaotic (c) Random Data**

Finally, the last statistical test to be made is the probability distribution, which shows frequency of observation of a certain data value (x). The knowledge of probability distribution is necessary because it provides important information about the possible characteristics of the underlying time series. For instance, a periodic time series will show a few peaks.

A chaotic time series, on the other hand, will show a normal or Maxwellian distribution, whilst a random one will show a relatively flat distribution. Figure 6-4 illustrates the above differences.

To sum up, a good description of the variable being analysed is necessary in order to provide preliminary information about the time series being examined and to establish the background for further exploratory analysis. As was mentioned in the previous chapter, in exploratory analysis the data guides the choice of the analysis. Plotting the variable examined against time can give information on the behavioural patterns of the series. Sudden or cyclical changes, trends or irregular fluctuations can be spotted. Finally, the probability distribution plot can provide more information on the type of series.

It should be kept in mind that this stage only gives indications of the patterns of the behaviour rather than drawing final conclusions. It is a necessary step (to be used later) in order to compare the results of chaos analysis with those of the traditional statistical methods.

6.4 Phase II: Search for Correlations

The next phase of the data analysis is the search for correlations also known as measures of association or dependencies. The auto-correlation function is used to search for relationships between points in a time series. The results of the search can be split into four cases (Table 6-1); 1) no correlation, indicating that the time series is totally random, 2) correlation indicating that the data has a non-linear dependence, but shows no linear behaviour, 3) correlation showing that the data is linear with no non-linear behaviour, and 4) correlation indicating that the data shows both linear and non-linear dependence. In summary, the auto-correlation function is a strong test for looking for randomness in a time series.

To further analyse the time series, a time-delay auto-correlation function can be used in conjunction with a BDS statistical search, the power spectrum of the data, and finally by mutual information test.

6.4.1 Autocorrelation

The autocorrelation is another descriptive statistical technique. The importance of the autocorrelation function is that it can provide some information about the time evolution of the system and reflect the type of correlations. The autocorrelation coefficient measures the correlation of different observations at different distances apart. In the case of successive observations, the calculation of their correlation coefficient is described below.

For N number of observations $(x_1,\ldots,x_N)$, N-1 pairs of observations can be formed, (x_1, x_2), (x_2,x_3),…(x_{n-1}, x_N).

	Linear Correlations	Nonlinear Correlations	
Case 1	No	No	White Noise
Case 2	No	Yes	Non-Linearity
Case 3	Yes	No	Linearity
Case 4	Yes	Yes	Chaos

Table 6-1: **Possible Autocorrelation Function Outcomes**

If the first observation of each pair is considered as one variable, the second as a second variable and so on, the correlation coefficient between variables x_t and x_{t+1} can be estimated in approximation as (Chatfield, 1989):

$$r_1 = \frac{\sum_{t=1}^{N-1}(x_t - \bar{x})(x_{t+1} - \bar{x})}{(N-1)\sum_{t=1}^{N}(x_t - \bar{x})^2 / N}$$

where, r is the auto-correlation coefficient and $\bar{x}$ is the mean value of x, which is calculated as:

$$\bar{x} = \sum_{t=1}^{N} x_t / N$$

The autocorrelation coefficient at distance, or lag, k apart is similarly calculated as:

$$r_k = \frac{\sum_{t=1}^{N-k}(x_t - \bar{x})(x_{t+k} - \bar{x})}{\sum_{t=1}^{N}(x_t - \bar{x})^2}$$

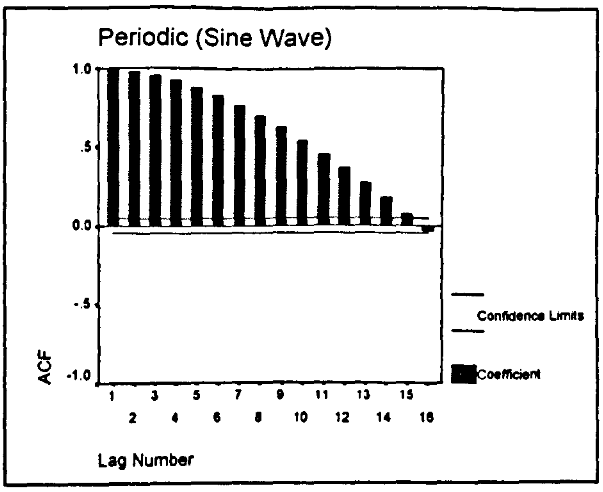
One way to analyse the auto-correlation function is to plot r_k as a function of k, in a plot known as a *correlogram.* Chatfield explains the interpretation of correlogram using six common cases; random time series, short-term correlation, periodic time series, non-stationary time series, seasonal fluctuations and outliers (Chatfield, 1989: 20-24). He comments that if all of r_k lie close to zero (within $\pm 2/\sqrt{N}$ of zero) then the series is assumed to be random (no correlation). A time series with short-term correlation is recognised by noting that for low values of k, r_k is close to unity, but as k increases, r_k decreases, converging towards zero for large k values. Periodic series show a shift from positive values of r_k to negative values, with a frequency equal to that of the time series frequency. The same is also true for seasonal drift, where the value of r_k fluctuates at the same frequency as the seasonal changes. In the case of a fluctuating time series superimposed on a slowly changing term, the value of r_k will not converge to zero, except for very large values of k. This type of time series is known as non-stationary. Finally the presence of *outliers* (points which do not appear to *fit in* with the rest of the data, for example due to a measurement error) can severely influence the results, and as such must be removed from the data set before analysis.

Figure 6-5 illustrates the three cases of periodic, chaotic and random time series. In the case of random series the autocorrelation will tend to decay. The rate of the decay is dependent on the properties of the system. In the case of deterministic series the decay will be exponential with an increase in time lag k. Finally, it is important to mention that the autocorrelation by itself is not enough to separate a chaotic from a random series (Kanzt & Schreiber, 1997: 19).

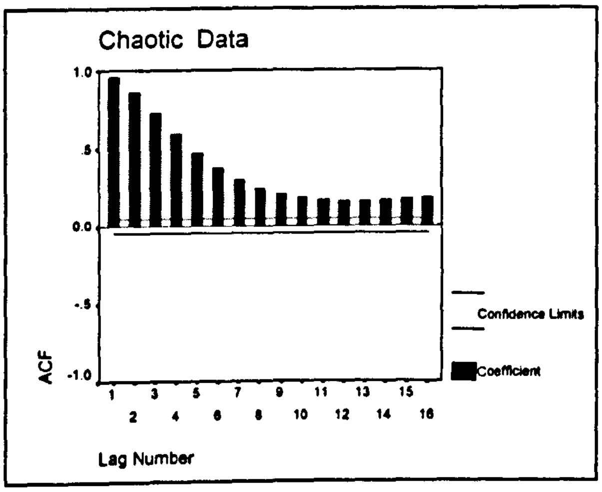
6.4.2 Power Spectrum

The Power Spectrum is a complementary diagnostic tool for time series analysis along with the data plot and autocorrelation. This technique analyses the data in frequency space, as opposed to time, by calculating the frequency spectrum of the data (Chatfield, 1996: 105). According to Kanzt & Schreiber,

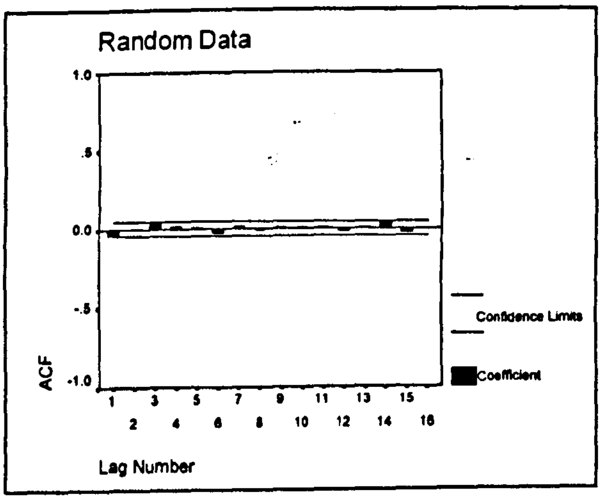
> *The Fourier Transform establishes a one-to-one correspondence between the signal at certain times (time domain) and how certain frequencies contribute to the signal, and how the phases of the oscillations are related to the phase of other oscillations (frequency domain)* (Kanzt & Schreiber, 1997: 19).



(a)



(b)



(c)

Figure 6-5: **Correlograms (a) Periodic (b) Chaotic (c) Random**

The philosophy behind the Power Spectrum is that the nature of a function can be either periodic or non-periodic (Baker & Gollub, 1990: 28-36). Thus, for any periodic time series, its evolution in time can be represented as a series of harmonic functions of different amplitudes. This mathematical tool was first demonstrated by Fourier, and can be represented as follows:

$$f(t) = \sum_{n=-\infty}^{\infty} a_n e^{in\omega_o t}$$

Where, a_n are the amplitudes of the components at frequency $n\omega_0$.

For instance, if the function $f(t)=f(t + nT)$ is periodic with T being the basic periodicity and n being a positive or negative integer, the frequencies of the various spectral components are all integer multiples of the basic frequency ($1/T=\omega_o/2\pi$).

In the case of a non-periodic function, the periodicity of $f(t)$ becomes infinitely large and a Fourier Transform must be applied. In other words the system appears to fluctuate and becomes unstable. A technique used to perform such an analysis is the Fast Fourier Transform (Colley, Lewis & Welch, 1967). It is considered the most accurate technique (Chatfield, 1996: 118). It is a non-parametric method in the sense that there is no *a priori* model. Importantly, any trend or seasonality in the data should be removed beforehand as it can distort the results.

Figure 6-6 shows the differences of a periodic, chaotic and random set of data in the power spectrum. As can be observed from the graphs, the power spectrum of a periodic series will show a few dominant peaks.

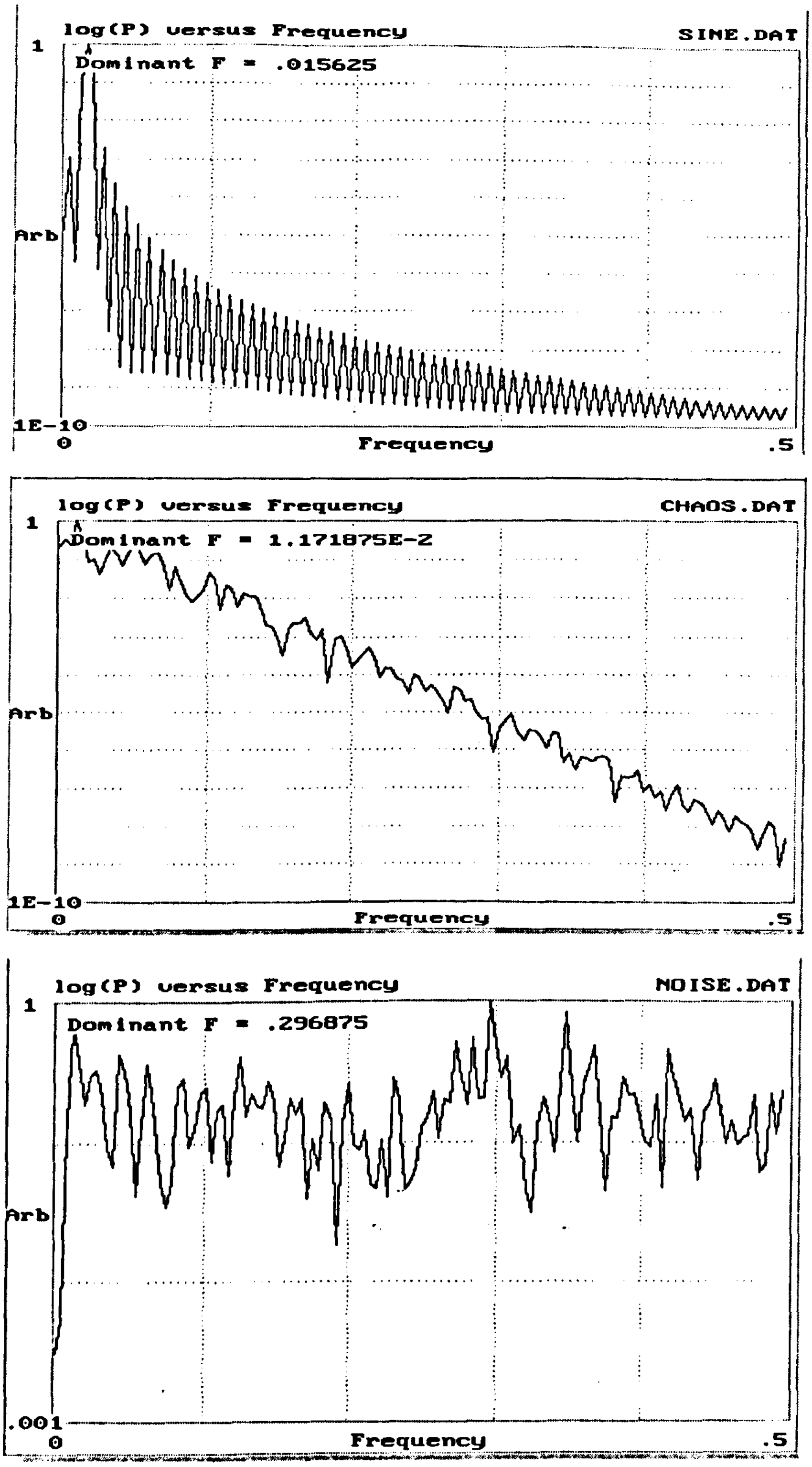


Figure 6-6: Power Spectrum of (a) Periodic (b) Chaotic (c) Random Data

The power spectrum of a chaotic series in a log-linear scale will tend to be a straight line since noise tends to have a power-law spectrum. Similarly, a random series will be flat, producing a broad spectrum.

6.4.3 Detection of Nonlinear Dependencies: The BDS Test

The first test to be performed is the test for non-linear dependencies in the time series. There are several tests for nonlinearity including those developed by McLeod & Li (1983), Tsay (1986), Hinich (1982), Hinich & Patterson (1985), and Hsieh (Hsieh, 1989). However, the most commonly used test is the BDS statistics test, developed by Brock, Dechert & Scheinkman (Brock, Dechert & Scheinkman, 1987; Brock, Hsieh & LeBaron, 1991). The BDS statistic was developed to detect the existence of nonlinear dynamics and it tests for independence and identically distributed (i.i.d.) data of the time series.

It was designed to test the characteristics of a particular variable by making use of the correlation integral (Grassberger & Procaccia, 1983), which was initially developed for studying low-dimension chaos in time series in physics applications. Examples of applications of the BDS test examining non-linearity in time series can be easily found in many different disciplines (Clyde & Osler, 1997; Hsieh, 1989; Kiel & Seldon, 1998; Thiétart, Forgues, 1997).

As it was mentioned above, the BDS test is based on the correlation integral. More specifically, taking a series of observations of variable *x(t)* that are independent and identically distributed, the predecessors of x_t are $x_{t-1}, x_{t-2}, \ldots x_{t-n}$, where n is the number of periods back in time. The variable x_t can then grouped with at least one of its predecessors into a vector, forming a series of N-dimensional vectors $x_t^N = (x_t, x_{t+1}, \ldots, x_{t+N-1})$, the so-called "$N$-histories". Then the correlation integral is calculated according to the following formula:

$$c_N(\ell,T)=\frac{2}{T_N(T_N-1)}\sum_{t<s}I_\ell(x_t^N,x_s^N)$$

The correlation integral $c_N(\ell,T)$ calculates the number of pairs of such vectors of observations $\{x_t\}$ and its predecessor(s), which lie within a certain distance ℓ of each other over time T. The $I_\ell(x_t^N,x_s^N)$ is an indicator function that equals zero in all cases except when $\|x_t^N-x_s^N\|<\ell$ where it is equal to one. Thus, the correlation integral estimates the probability that any two vectors of N-histories, $x_t^N=(x_t,x_{t+1},\dots,x_{t+N-1})$ and $x_s^N=(x_s,x_{s+1},\dots,x_{s+N-1})$, are within l of each other. When the x_t is independent for $|t - s| > N$, the correlation integral is:

$$c_N(\ell,T)\rightarrow\prod_{i=0}^{N-1}\ \text{prob}\{|x_{t+i}-x_{s+i}|<\ell\},\ \text{as}\ T\rightarrow\infty$$

When the x_t is also identically distributed then the correlation integral is:

$$c_N(\ell,T)\rightarrow c_1(\ell)^N,\ \text{as}\ T\rightarrow\infty$$

In other words, the BDS statistic gives some information about the type of dependence in the data. This information is obtained by looking at the probabilities of any pair of N-histories "clustering" in an N-dimensional space. In this way the possibility that the series analysed is random is minimised.

There are couple of important issues that should be considered while applying the BDS test. Both the distance or proximity parameter λ and the embedding dimension N have to be chosen by the researcher. First, if the chosen value of λ is too small, the null hypothesis of i.i.d. will be accepted too often irrespective of being true or false (Scheinkman & LeBaron, 1989). A small value of λ implies that the BDS result falls within the noise levels of the series. If the value of λ is large then there is a probability to overestimate the closeness of the data vectors. Finally, for greater values of chosen N there is a risk of underestimating the "true" value of correlation function (Medio, 1992: 260). In order to avoid these pitfalls there are some guidelines in order to select the values for both λ and N. Brock *et al* suggests the N-dimensional distances λ should be based on the standard deviation of the x, denoted σ_x, and the range, or spread, of the data, denoted S (Brock, Hsieh & LeBaron, 1991). The λ should range from $0.5(\sigma_x/S)$ to $2(\sigma_x/S)$. For instance, for a two-sided test and 95% confidence, 39 shuffled data sets should be made. All these issues are taken into consideration when the BDS Statistics test is applied on the underlying data set (Chapter 7 & Chapter 8).

Finally, there are three main attributes of the BDS statistics test. First, it has "power against simple non-linear deterministic systems as well as non-linear stochastic processes" (Hsieh, 1989). It tests the null hypothesis that the data are independently and identically distributed in an observed time series. If the null hypothesis is rejected, then the series is non-linear. If it is not rejected the phenomenon is random. Second, it tests the hypothesis for random independent and identically distributed systems. If the null hypothesis is rejected then there is some type of dependence in the data, which could result from a linear stochastic system, a non-linear stochastic system, or a non-linear deterministic system. In this case, additional diagnostic tests are needed to determine the source of rejection.

6.4.4 Mutual Information Test

The Mutual Information test has the same function as the autocorrelation function but instead of searching for only linear correlations it considers also non-linear correlations. Mutual information was developed by Fraser & Swinney (1986) and is computed as:

$$S = -\sum_{ij} p_{ij}(t) \ln \frac{p_{ij}(t)}{p_i p_j}$$

where, p_i is probability of finding a value in the i-th interval and $p_{ij}(t)$ is the joint probability that a particular value is in i-th interval and the same value is also in the j-th. A more detailed and complete description of mutual information statistics can be found in Kanzt & Schreiber (1997). Briefly, this test calculates the "Shannon entropy", which is measured in order to either determine the degree of uncertainty, or as a measure of the rate of information acquisition. When the Shannon entropy is equal to zero, it means that there is high uncertainty about the outcome.

6.5 Surrogate Data Test I

In general, the importance of the surrogate data test is to "discriminate non-linear dynamics, if this can be detected from the given time series" (Kugiumtzis, 2001). It deals with two null hypotheses for the observed data. The first one is that the time series is simply white noise, and second, that it involves only temporal linear stochastic correlations. The rejection of these two possibilities is of importance because it excludes the final possibility that the results of the above analysis might have been coincidental. If those cases are excluded then the possibility of chaotic behaviour is almost certain. In addition, this test is very important in the analysis of short-time series because it increases the evidence of chaotic behaviour. Nevertheless, surrogate data test raises a few issues as with any other test. Those involve the non-linear discriminating statistics, and certain characteristics of the time series, such as stationarity (Schreiber & Schmitz, 2000; Timmer, 1998; Kugiumtzis, 2000).

The statistical hypothesis of the surrogate data test is composed of the null hypotheses H_0 and the discriminating statistic q. The discriminating statistic is the one that determines whether the null hypothesis will be rejected or not. It is an estimate of the data characteristic and its variation. The Surrogate Data Test I deals with the first hypothesis tests for white noise. The null hypothesis H_0 is that the observed correlations $\{x_i\}$, $i=1, \ldots, N$, are uncorrelated. In other words, it looks whether the system is white noise or otherwise has no memory between successive data points to another. The surrogate data for this hypothesis testing are simple permutations of the original data, called scrambled surrogates (Kugiumtzis, 2000; Kanzt & Schreiber, 1997). The second hypothesis is investigated in Surrogate Data Tests II, which is explained in Section 6.7.

6.6 Phase III: Characteristics of the Underlying System

As mentioned in Chapter 4, the main criteria for a system to be characterised as chaotic are; to be aperiodic, bounded, have sensitivity to initial conditions and structure in phase space. This section explains the mathematical calculations behind the phase space, correlation dimension, Lyapunov exponent and Hurst exponent.

6.6.1 Phase Space

The evolution in time of a dynamic system can be represented in phase space. Phase space specifies the state of the system, and vice versa (Kunzt & Schreiber, 1997: 29-30). If the phase space is a finite-dimensional vector space $\Re^m$, and the time is a discrete variable then the dynamics can be described by an m-dimensional map, as:

$$x_{n+1} = F(x_n), \quad n \in \Re$$

If, however, the phase space is a finite-dimensional vector space $\mathfrak{R}^m$, and the time is a continuous variable then the dynamics can be described by an explicit system of *m* first-order ordinary differential equations, such as:

$$\frac{d}{dt}x(t) = f(t, x(t)),$$

with $t \in \mathfrak{R}$. In this case phase space plots are usually of dx/dt as a function of $x(t)$. This type of plot is important because it can unfold the multidimensional structure of the series and provide better insights in the data's behaviour by identifying, if any, the attractors of the system.

An attractor is "a pictorial map of the ensuing chaos." (Jenkins, 1998: 10). The shape of the basin of the attractor, determines the general behaviour of objects, which "randomly" roll around inside of it. For instance, Figure 6-7 illustrates the differences between a periodic, chaotic, and random time series. According to the plots a closed loop implies a periodic system, a discernible structure proposes possible simple chaotic system, and a no discernible structure shows possible randomness (Sprott & Rowlands, 1995).

According to Thompson & Steward there are three types of attractors, point, periodic, and chaotic attractor (Thompson & Steward, 1986). *Point attractors* display precise dynamics that are attracted to the same point in each cycle that occurs in time-space. *Periodic attractors* are attracted within precise limits above and below which the behaviour of a dynamical system does not exceed. There are different types of chaotic attractors. For instance, *torus* is a two-dimensional surface with one outcome basin. This type of attractor replaces sameness with self-similarity.

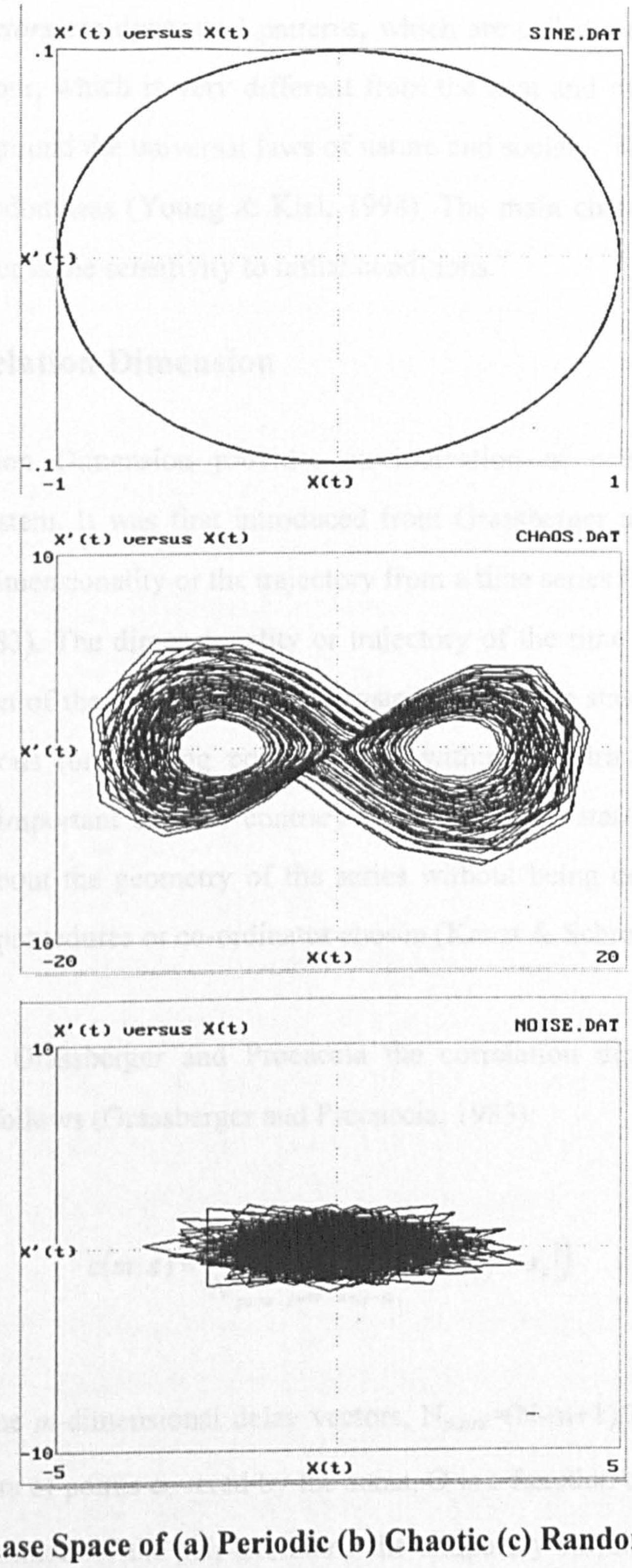


Figure 6-7: **Phase Space of (a) Periodic (b) Chaotic (c) Random Behaviour**

Strange attractors are dynamical patterns, which are called strange since they depict behaviour, which is very different from the neat and orderly behaviour presumed to ground the universal laws of nature and society. The type of chaos is close to randomness (Young & Kiel, 1994). The main characteristic of this type of attractor is the sensitivity to initial conditions.

6.6.2 Correlation Dimension

The Correlation Dimension provides an indication of complexity in the underlying system. It was first introduced from Grassberger and Procaccia to measure the dimensionality or the trajectory from a time series (Grassberger and Procaccia, 1983). The dimensionality or trajectory of the time series is simply the progression of the positions that the system fills in the state space from its initial conditions (or, starting point) to and within its attractor. Correlation dimension is important because contrary to other *ad hoc* statistics it provides information about the geometry of the series without being dependent on the measurement procedures or co-ordinates chosen (Kanzt & Schreiber, 1997: 72).

According to Grassberger and Procaccia the correlation dimension can be calculated as follows (Grassberger and Procaccia, 1983):

$$c(m,\varepsilon)=\frac{1}{N_{pairs}}\sum_{j=m}^{N}\sum_{k<j-\omega}\Theta\left(\varepsilon-\left|s_j-s_k\right|\right)$$

where s_i are the m-dimensional delay vectors, N_{pairs}=(N-m+1)(N-m-ω+1)/2 the number of pairs of points covered by the sums, Θ is a function called Heaviside and ω is an estimate of the pair excluding the temporary correlated points (e.g. the first zero in the autocorrelation) as proposed by Theiler (Theiler, 1986). It has to be mentioned that before the computation of the Correlation Dimension a phase space should be constructed spanned by a set of embedding vectors.

6.6.3 Lyapunov Exponent

Unpredictability of future events despite the deterministic time evolution, the so-called sensitivity to initial conditions, is one of the main characteristics of chaotic systems. Deterministic systems can be categorised as regular or chaotic, depending on the relative behaviour of groups of its possible paths. Regular systems have their neighbouring paths (or trajectories) staying close to each other as they evolve, diverging, at most, linearly with time (Auyang, 1998: 233). The Lyapunov exponent quantifies this rate of divergence and can be defined as "the mean exponential rate of separation as time goes to infinity for paths that are initially within an infinitesimal region of each other" (Auyang, 1998: 133).

The Lyapunov exponent, measures the mean exponential rate of divergence of initially close orbits (one exponent for each direction of the phase-space axes). Regular systems have a periodic orbit and negative Lyapunov exponent. Systems near birfucation have a zero Lyapunov exponent. In these systems, disturbances will grow in time turning the system highly unstable, which is an element of chaos. Thus, the usefulness of the Lyapunov exponents is to "characterise dynamical systems" (Tabor, 1989: 148) and to test the system for chaotic motion, specifically for sensitivity to initial conditions.

There are several ways to calculate the Lyapunov exponent (Kanzt & Schreiber, 1997; Rosenstein, Collins & Deluca, 1993; Wolf, Swift, Swinney & Vastano, 1985). The Rosenstein method proposes the calculation of the largest Lyapunov exponent for short and noisy time series[1]. It should be mentioned that the number of possible Lyapunov exponents that can be estimated is as many as the phase-space dimensions. The one that holds most importance is the maximum

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[1] This method matches better the characteristics of the data analysed in this thesis.

Lyapunov exponent (λ). That is because it is the only one that can determine whether the system is characterised by chaotic dynamics or not (Kanzt & Schreiber, 1997).

There are three steps for the calculation. First, the phase space is constructed. Then the nearest neighbour for each vector is found. Finally, the largest Lyapunov exponent is calculated as described below.

If the distance between two neighbours at time t, with initial separation C, is equal to

$$d(t) \sim C\, e^{\lambda t}$$

then taking by the natural algorithm from both sides, a set of different parallel lines for different embedding dimensions is calculated:

$$\ln d(t) \sim \ln C + \lambda t$$

The largest Lyapunov exponent is the mean slope, averaging over all the embedding vectors. A list of the potential results that the largest Lyaponov exponent can give is shown in Table 6-2.

Type of Motion	**Maximum Lyapunov Exponent**
Stable fixed point	$\lambda<0$
Stable limit cycle	$\lambda=0$
Chaos	$0<\lambda<\infty$
Noise	$\lambda=\infty$

Table 6-2: **Potential Results of the Maximum Lyapunov Exponent**

6.6.4 Hurst Exponent

The purpose of this method is to search for cyclical behaviour in the time series and check the type of "cumulative memory" for all preceding events. It was named after its founder H.E. Hurst, a hydrologist studying the Nile River Dam Project in early 1900s. The focus of his research was to explain the behaviour of the annual overflow phenomenon, which at that time was considered to be a random process. The investigation of Hurst exponent has two benefits. First, it shows whether the time series data shows cyclical behaviour, and second it measures a kind of "cumulative memory" of all preceding events.

Hurst exponent measures of the smoothness of fractal time series based on the asymptotic behaviour of the rescaled range of the process. In mathematical terms it estimates the extent to which the data can be represented by a random walk (fractional Brownian motion). Hurst came up with the equation:

$$R/S = kn^{\mathrm{H}}$$

where R/S is the rescaled range (range/standard deviation), n is the number of observations, k is a constant, and H is the Hurst exponent. The ingeniousness of this equation is that it can be applied to any time series regardless of the underlying distribution of the data. This independence on constraints on the traditional random walk model allows the search for "hidden" cyclical behaviour in any time series.

Based on Hurst's equation the Hurst exponent can be calculated as:

$$H = \log(R/S) / \log(t)$$

where t is time - the duration of the sample of data. In this way Hurst generalized an equation valid for the Brownian motion in order to include a broader class of time-series. In fact, Einstein found that the distance R covered by a particle undergoing random collisions is directly proportional to the square-root of time *(t)*:

$$R \propto t^{1/2}$$

The Hurst exponent can be equal, greater or smaller than 0.5. The integral of white (uncorrelated) noise corresponds to ordinary Brownian motion and has a Hurst exponent of 0.5. Hence, if H = 0.5 then the time series is similar to a random walk or otherwise is *random.* Exponents greater that 0.5 indicate persistence (past trends persists into the future). For example, if the fluctuation in the time series increase then the Hurst exponent will tend to increase and vice versa, when the fluctuations decrease the Hurst exponent will tend to decrease. A Hurst exponent of less than 0.5 indicates anti-persistence (past trends tend to reverse in the future). Thus, if you have data with a relatively flat power spectrum, one might integrate it and see if the exponent is close to 0.5, which would imply that it is random and uncorrelated. In this way, the benefits of this method are two. The first benefit is to point to a long-term possible infinite memory. Second it can be applied to any time series regardless the underlying distribution of the data (von Rönik, 1997), possibly revealing in this way "secret" decision patterns that can assist to understand better the behaviour of the data.

6.7 The Surrogate Data Test II

In Section was mentioned that the importance of the surrogate data test is to discriminate non-linear dynamics (Kugiumtzis, 2001). While the hypothesis for white noise was then investigated in Surrogate Data Test I, Surrogate Data Test II examines the second hypothesis for temporal linear behaviour. Thus, having rejected the possibility of independence the next step is to investigate the nature of those correlations. In order to do this a null hypothesis H_0 should be formulated testing for temporal linear stochastic correlations. That means that the data was generated by linear stochastic process with Gaussian increments. The most attractive way to test H_0 is to create constraints realisations or create the so-called Fourier Transform surrogates (Kugiumtzis, 2000; Kanzt & Schreiber, 1997). The surrogate data for this hypothesis testing is generated using the Amplitude–Adjusted Fourier Transform (AAFT) algorithm (Kugiumtzis, 2000; Kanzt & Schreiber, 1997).

Finally, the level of significance determines the probability of hypothesis rejection. The decision of the level of significance in the surrogate data test is very important because it determines the number of surrogate data sets that should be composed. For instance, if the aiming target is 95% level of significance only 5% of chance (α=0.05) is allowed. This estimation is based on the rank-order test (Theiler, Eubank, Longtin, Galdrikian & Farmer, 1992). According to the test, first a residual probability α of a false rejection is selected corresponding to a level of significance (1-α) x 100%. For a one-sided test (looking for small prediction errors only) $M = 1/\alpha - 1$ surrogate sequences should be generated. These surrogate data sets, including the original set, count for $1/\alpha$ sets, resulting in the probability α that the data by coincidence has the smallest prediction error. For a two sided-test (e.g. for time asymmetry which can go both ways), $M = 2/\alpha - 1$ surrogate data sets should be generated, resulting in a probability α that the data gives either the smallest or the largest value (Schreiber & Schmitz, 2001). The number of surrogate data sets generated for the data analysis of this thesis is based on the above explanation. Thus, in order to achieve 95% level of confidence 39 surrogate data sets were generated.

6.8 Validity, Reliability & Pitfalls in Data Analysis

There are two main pitfalls that could shake the validity and reliability of the data analysis. Firstly, some of the methods of chaos theory analysis, such as Lyapunov exponent require a large number of data points. Thus, applying methods of chaos theory to short-time series might be criticised. In order to minimise this criticism the surrogate data test is performed.

6.9 Summary

To sum up, the purpose of the data analysis is to investigate whether the high fluctuations in demand could be explored and explained via the non-linear methods of chaos theory. There are three phases in the data analysis. The first phase called the pseudo-state space the purpose of which is to read the data. In other words it is used to show that the data has been recorded properly. The second phase is the correlation or dependency phase. The purpose of this phase is to search for correlations in the data; linear, non-linear or general correlations. The third phase estimates the characteristics of the underlying system. Finally, the surrogate data test is performed at the end of Phase I and Phase II in order to increase the validity of the results.

PART IV

RESULTS

Chapter 7

Results (Part I)

Chapter 7:

Results (Part I)

This chapter presents the results of the data analysis. The structure of the chapter follows the CASTS framework. First, the data is described, then a search for correlations is applied and finally, potential signs of chaos are explored. At the end, a summary of the results is given.

7.1 Introduction

The purpose of this chapter is to present the results coming from the application of CASTS to analyse the data. The data represents the quantity ordered for distribution, in number of cases (logistics demand), in a time series format. The data used in this analysis was extracted from the files of EXEL/FORD Logistics. A sample of approximately two and a half years, or a total of 930 days, was examined. In Section 5.5.4 it was mentioned that a certain preparation was needed on the data before proceeding to further analysis: aggregation and elimination of the weekends. The original format of the data was given per customer per day. Thus, an aggregation of the data, in total quantity per day, was performed. The graph of the raw data, after the aggregation, is shown in Figure 7-1. The C code used for the aggregation can be found in Appendix 1.

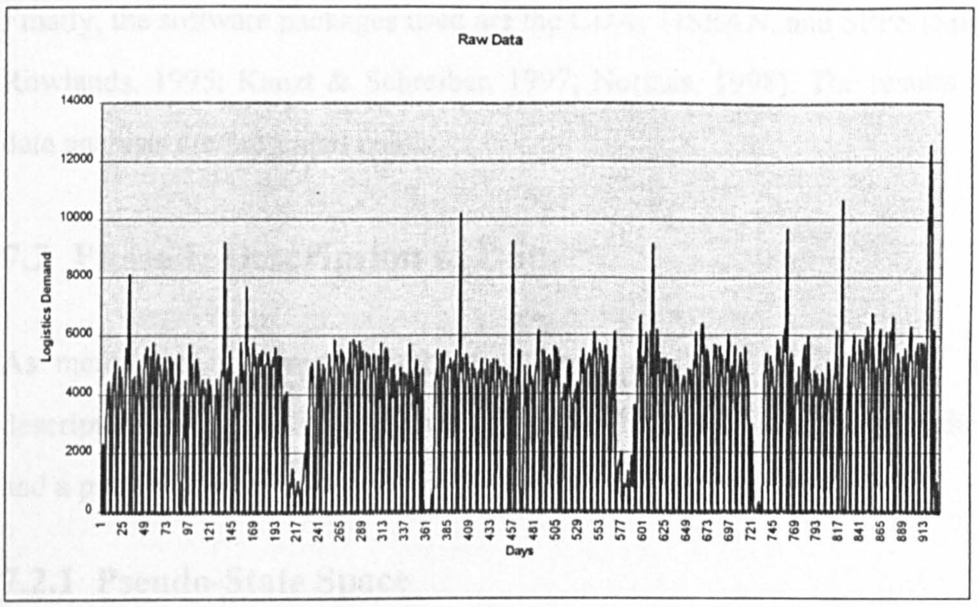

Figure 7-1: **Graph of the Raw Data**

It can be seen from the graph that the "close down weekend" effect creates a lot of noise and should be eliminated before further analysis. Such elimination will make little impact on the results. The company is closed at the weekends and thus, no new orders are coming in. As a result, Friday's demand activities are correlated to Monday's.

It should be noticed that the weekends were not included in the analysis (Figure 7-2).

Finally, the software packages used are the CDA, TISEAN, and SPPS (Sprott & Rowlands, 1995; Kanzt & Schreiber, 1997; Norusis, 1998). The results of the data analysis are presented below.

7.2 Phase I: Description of Data

As mentioned in Chapter 6, the first phase of the CASTS method is the description of the underlying data. This phase involves the plotting of the data and a presentation of the summary of the descriptive statistics.

7.2.1 Pseudo-State Space

The plot of the data is also known as the plot of pseudo-state space. The purpose of this graph is to represent the quantity x again the time t. This graph provides two types of information. First, it illustrates the behaviour of the underlying data with time. Second, it can illustrate outliers or seasonal effects that may need to be removed before the further analysis of the data. Figure 7-2 shows that there are still quite a few peaks and dips on the graph. The two main dips are the result of the company's shut down during Christmas. For that reason the data is detrended.

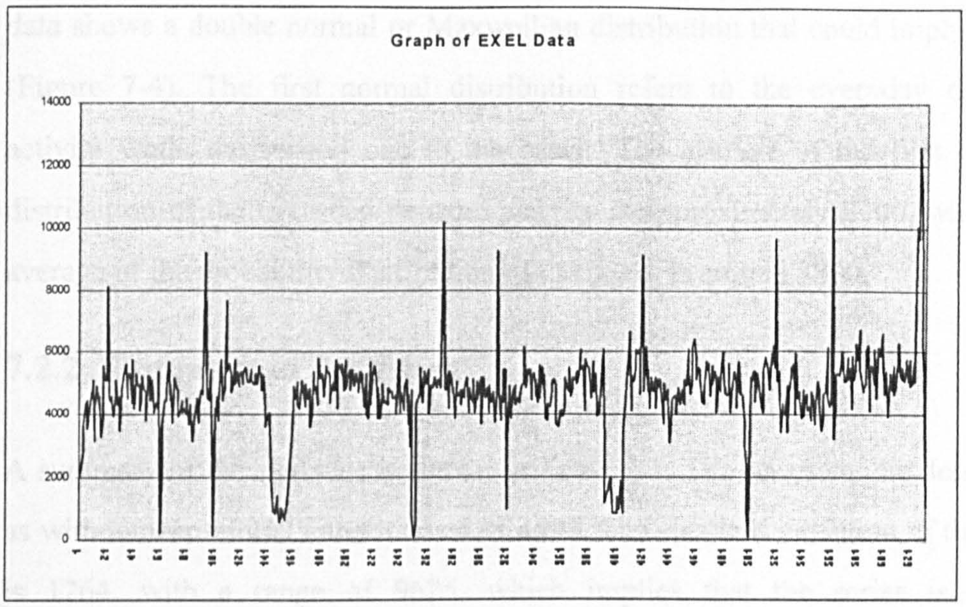

Figure 7-2: **Pseudo-State Space**

The data shows no particular repeating trend. There are two main dips, which are the result of the shut down of the company for Christmas.

Figure 7-3 shows a plot of the detrended data set. As can be seen there are still a lot of the peaks and dips in the series. These peaks seem to be spread in time following no particular pattern. The probability distribution of the detrended data shows a double normal or Maxwellian distribution that could imply chaos (Figure 7-4). The first normal distribution refers to the everyday demand activity while the second one to the peaks. The average of the first normal distribution of the everyday demand activity is approximately 2300, while the average of the probability distribution of the peaks is around 3800.

7.2.2 Summary of Statistics

A summary of the statistics is shown in Table 7-1. The series can be described as with a mean of 4623 and median of 4594. The standard deviation of the data is 1264, with a range of 9625, which implies that the series is rather heterogeneous (see Chapter 6). The shape of the series is negatively skewed and peaky. The skewness is measured to be –1.002 entailing a negative deviation from symmetry. The kurtosis, on the other hand, is estimated to be 4.201 meaning peakiness.

7.3 Phase II: Search for Correlations

This phase searches for linear and non-linear correlations in the data. In other words, it tests the hypothesis that the system is not white noise. Phase II consists of the four linear and non-linear tests. Those are the autocorrelation, power spectrum, mutual information and BDS statistics test.

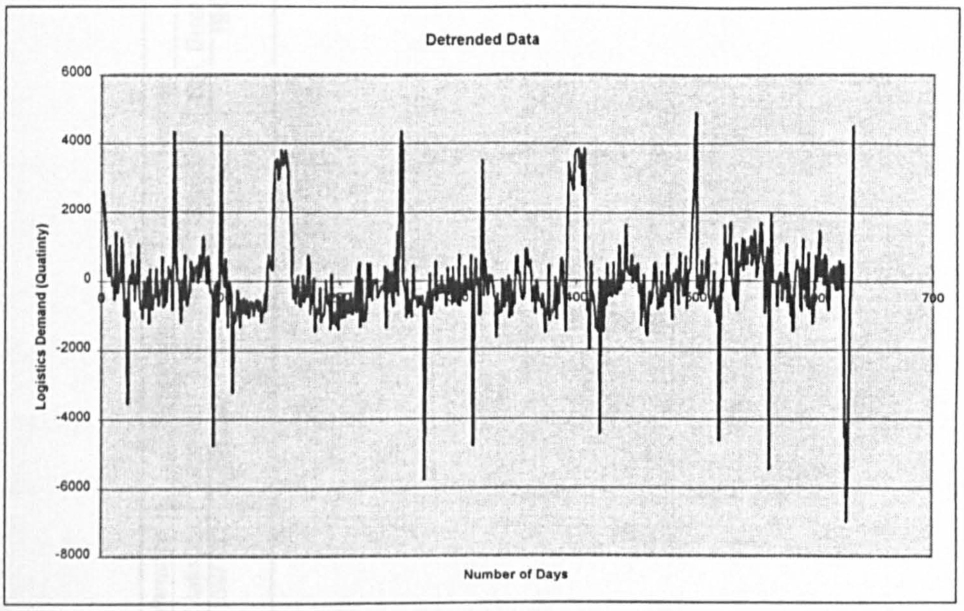

Figure 7-3: **Graph of the Detrended Data**

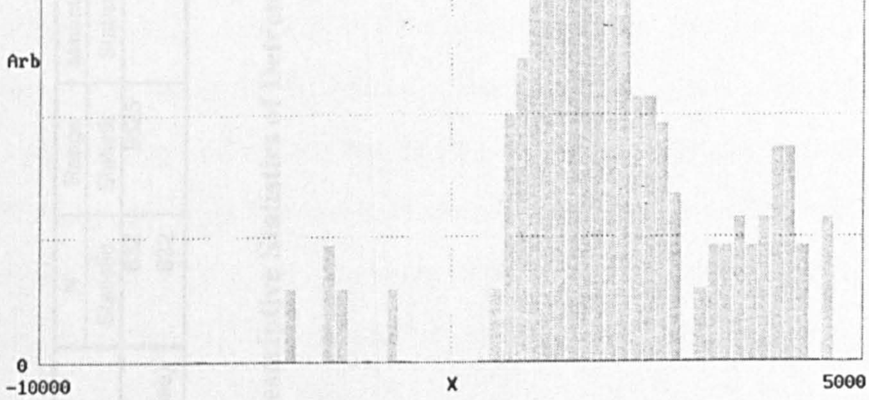

Figure 7-4: **Probability Distribution of Detrended Data**

Descriptive Statistics

	N	Range	Minimum	Maximum	Mean	Std.	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
EXELNZ	632	9625	59	9684	4623.02	1264.00	1597702	-1.002	.097	4.201	.194
Valid N (listwise)	632										

Table 7-1: **Descriptive Statistics of Detrended Data**

7.3.1 Autocorrelation

The autocorrelation function searches for linear correlations in the data. The purpose of the autocorrelation is to describe the tendency for nearby points in space or in time to exhibit similar characteristics. The correlogram of the data is shown in Figure 7-5. First, it can be noticed that the function is not close to zero. According to Chatfield (1997) a time series is considered to be random when the autocorrelation coefficient lies between $\pm 2/\sqrt{N}$. For this data set this value is approximately 0.06, which implies that the underlying data is not random. Another issue that can be observed from the figure is that the series distinctively shifts from positive to negative, implying two distinct data sets. However, the change between positive and negative values does not seem to follow a certain pattern, as it would do in linear series. The type of fluctuations seems to lead towards a non-stationary series. Nevertheless, no final conclusion can be made at this point because the number of these data sets in the series is very small, and therefore any statistical analysis would have large errors. Thus, the autocorrelation function has shown indications that the data is not linear and it seems not to be random either.

7.3.2 Power Spectrum

The power spectrum, contrary to the phase space plot, plots the data against frequency. It calculates the frequency spectrum of the data. Looking at Figure 7-6 the power spectrum pattern can be an indication of possible chaos, i.e. due to slight decay, or might be random if seen as flat, as discussed in Section 6.4.3 and illustrated in Figure 6-6. Knowing that the data is not random from the autocorrelation analysis, it is suggestive that the data shows signs of high-level chaos.

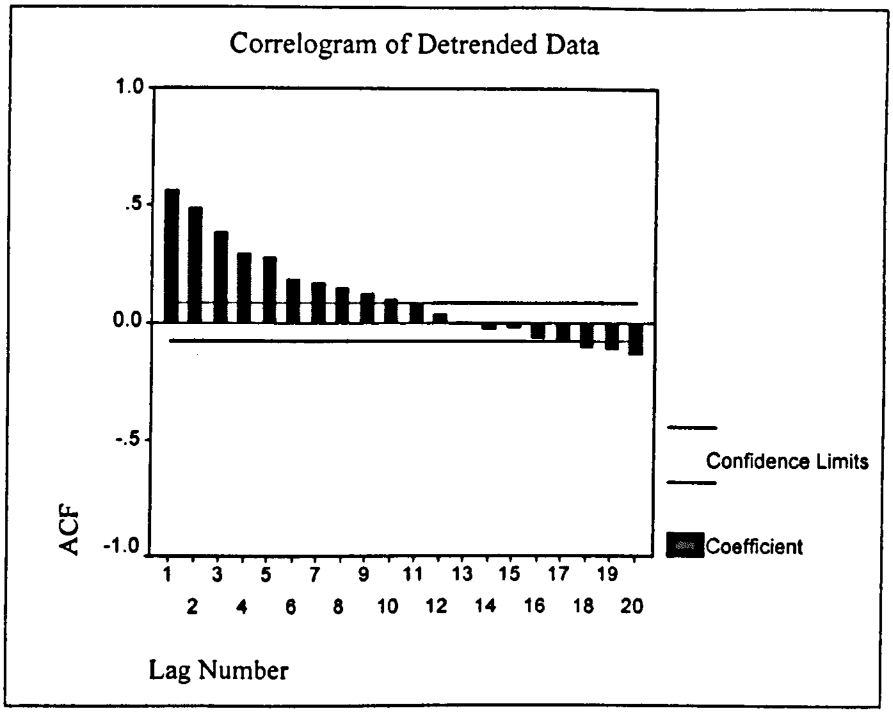

Figure 7-5: **Correlogram of Detrended Data**

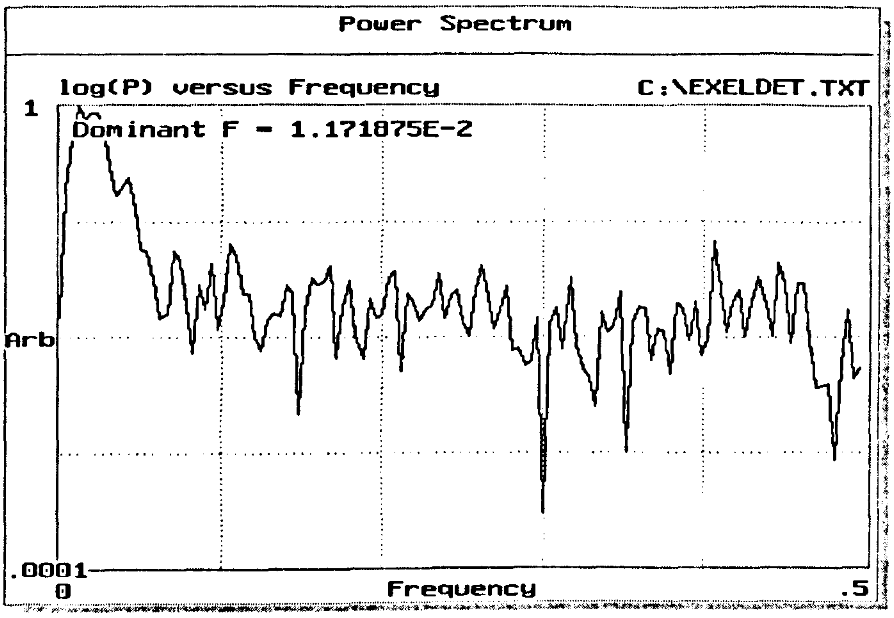

Figure 7-6: **Power Spectrum of Detrended Data**

That is not yet conclusive as short-time series data normally carry high levels of noise that may distort the results. So, further investigation is required.

7.3.3 BDS Statistics

As mentioned in Chapter 6, the purpose of BDS statistics is to test the hypothesis, H_0, for independent and identically distributed data points. In other words, it searches for non-linear correlations.

Two parameters should be determined before performing the test, the λ and N. The parameter λ is the nearest neighbour cutoff for the correlation integral calculation. Two points in space are neighbours if they are within the distance λ of each other. The real parameter λ should be between 0.5 and 2 times the standard deviation of the variable, divided by the spread or range of the data. In the previous section the standard deviation and the range were estimated to be 1264 and 9625 respectively. Therefore, the λ should be 0.0655, 0.1313, 0.1965 and 0.262. The second parameter N is the maximum embedding dimension to be considered and represents the ratio of observations to dimensions. The smaller the dimension λ is, the less complexity the system holds. The embedding dimension cannot be smaller than N=2 (Brock, Hsieh & LeBaron, 1991: 52). For the data set being analysed the maximum dimension is 3. Considering the above and using the CDA software package (Sprott & Rowlands, 1995), the results of the BDS test are summarised in Table 7-2.

According to the CDA results if the data is purely noisy the BDS statistics will be close to zero. If, on the other hand, the data is purely linear, the BDS statistic will be far from zero. The results of the analysis have shown the BDS statistic for the underlying data are closer to zero but not zero. Hence, the data cannot be linear and cannot be purely random.

N\n	1	2	4	8	16
2	0.339	0.118	-0.201	-0.733	-0.42
3	-0.192	-0.51	-1.083	-1.744	-1.4
4	-1	-1.174	-1.851	-2.388	-2.36
5	-1.58	-1.649	-2.244	-2.638	-3.086
6	-1.705	-1.771	-2.233	-2.463	-3.521
7	-1.612	-1.708	-2.011	-2.127	-3.551
8	-1.435	-1.527	-1.695	-1.74	-3.366
9	-1.216	-1.283	-1.371	-1.376	-2.995
10	-0.994	-1.028	-1.069	-1.054	-2.554

Table 7-2: **Results of BDS using CDA**

N = embedding dimension, n = time delay

To sum up, the results suggest that the null hypothesis of independent and identically distributed data points should be rejected. The rejection of the null hypothesis raises three possible outcomes; there are linear serial dependencies in the data; time series is non-stationary; and non-linear serial dependencies either stochastic or chaotic are present in the data.

7.3.4 Mutual Information

The mutual information technique looks for general correlations in the data. It is a way to determine useful delay co-ordinates for plotting attractors and it is a measure of the reduction in uncertainty for one random variable due to knowing another. In addition it is communication rate in the presence of noise.

The Figure 7-7 shows that as the time passes the level of information that is retained decreases. In other words, knowing what happened in the distant past will not help in determining the future. The Shannon entropy is calculated as mentioned in Section 6.4.4. When the Shannon entropy is equal to zero, it means that there is high uncertainty about the outcome. In other words, the further away from zero the Shannon entropy value is, the less the structure and the higher the uncertainty. The results are shown in Figure 7-7, from which we conclude that for a lag bigger than 3 the Shannon entropy is essentially zero and there is little certainty about future outcomes. For a lag smaller than 3 there is evidence of certainty in the behaviour of the system. This test has tremendous managerial implications as it can assist in defining the boundaries when the system changes behaviour and based on that, the time that the system stays on this behaviour could be calculated. This is further discussed in Chapter 10.

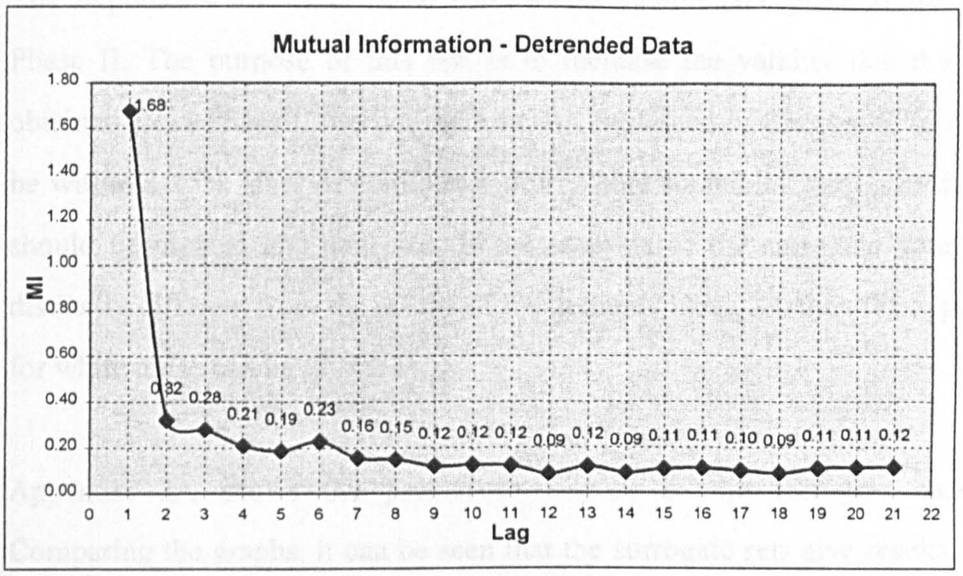

Figure 7-7: **Mutual Information Graph for Detrended Data**

7.4 Surrogate Data Test for White Noise

The hypothesis for white noise correlations should take place at the end of Phase II. The purpose of this test is to increase the validity that the results obtained from Phase II are not random. As explained in Chapter 6, in order to be within a 95% level of confidence, thirty-nine scrambled surrogate data sets should be created and analysed. If the analysis of the surrogate data sets is distinctly different from the results of the detrended data set, then the hypothesis for white noise can be rejected.

Appendix 2A shows the pseudo-state space of the surrogate data sets. Comparing the graphs, it can be seen that the surrogate sets give results, which are constantly different from the actual detrended data. It has to be mentioned that the probability distribution and the descriptive statistics are the same for the actual data and all the surrogate data sets. Next, the autocorrelation and power spectrum show that the surrogate data sets look random and different from the underlying data set (Appendix 2B & Appendix 2C). Finally, the BDS and mutual information tests show that the results of the data are different from those of the surrogate data. Figure 7-8 and Figure 7-9 illustrate that the results of the surrogate data sets lie far away from the result of the detrended raw data. In addition, Figure 7-10 shows the same result but for the mutual information test.

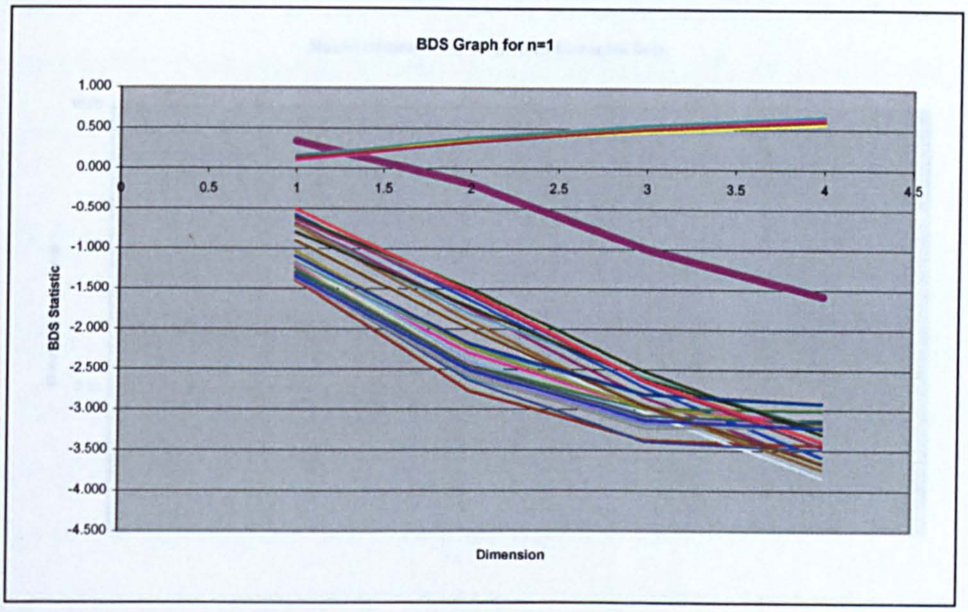

Figure 7-8: **BDS Statistic for $n = 1$**

The graph compares the BDS statistics results for delay $n = 1$ between the 39 surrogate data sets and the detrended data. The thick purple line represents the BDS statistics result of the detrentred data. The graph shows that all the results of surrogate data sets results are very different from those of the underlying data.

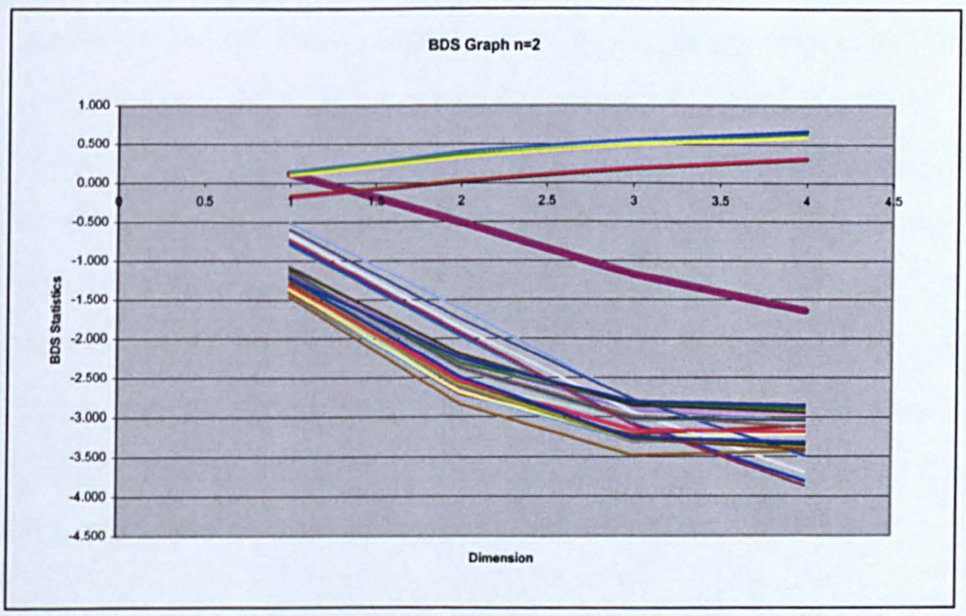

Figure 7-9: **Graph for BDS Statistic $n = 2$**

Similarly to the above graph, this graph also shows that all the results of surrogate data sets results are very different from those of the underlying data for delay $n = 2$.

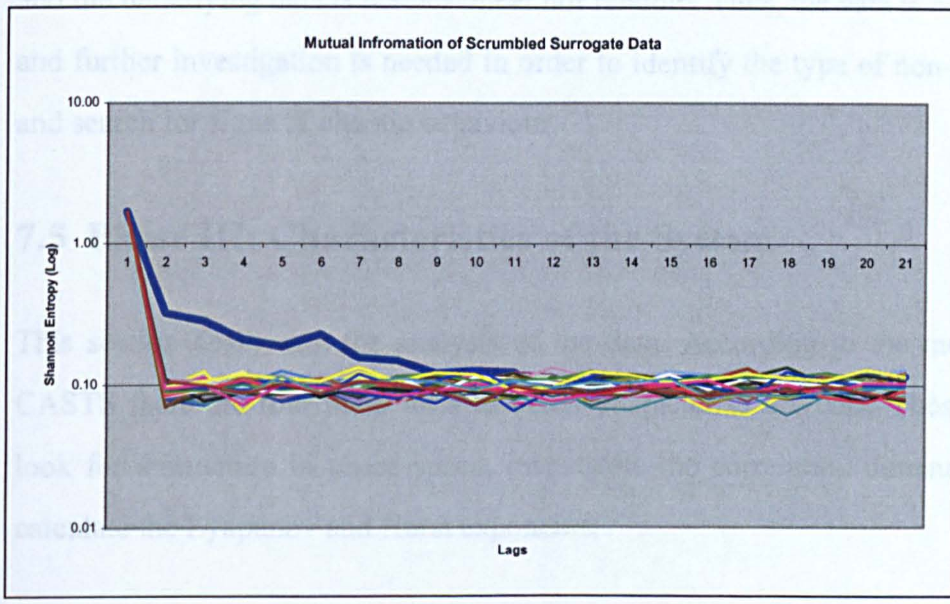

Figure 7-10: **Mutual Information for Scrambled Surrogate Data**

The graph compares the mutual information results between the 39 surrogate data sets and the detrended data. The thick blue line represents the results of the detrentred data. The graph shows that all the results of surrogate data sets results are very different from those of the underlying data.

It can be therefore safely concluded (with 95% confidence) that the hypothesis of white noise can be rejected. Thus, the results of Phase II analysis are correct and the underlying data is neither linear nor random. Thus, the data is non-linear and further investigation is needed in order to identify the type of non-linearity and search for signs of chaotic behaviour.

7.5 Phase III: Characteristics of the System

This section deals with the analysis of the data. According to the method of CASTS there are four main tests to better characterise the data. Those are to look for a structure in phase space, investigate the correlation dimension and calculate the Lyapunov and Hurst exponents.

7.5.1 Phase Space

The test represents the time evolution of the system by identifying its structure in phase space. The shape of the structure is what determines the general behaviour of the series examined. As shown in Figure 7-11, there are two distinct types of behaviour; a dense middle structure, which is a characteristic of random behaviour, and an orbiting structure suggesting the presence of a noisy periodic behaviour. Unfortunately, the number of points associated with the second type of behaviour is small and one cannot be more precise. It is suggestive however that this part of the data is periodic with a relatively large noisy component superimposed on it. A three-dimensional phase plane plot does not reveal a more unified structure. This is consistent with the comment above that the second type of behaviour is noise superimposed on a simple periodic structure. Finally, the above are consistent with the results shown in Figure 7-4, which identified two distinct distributions.

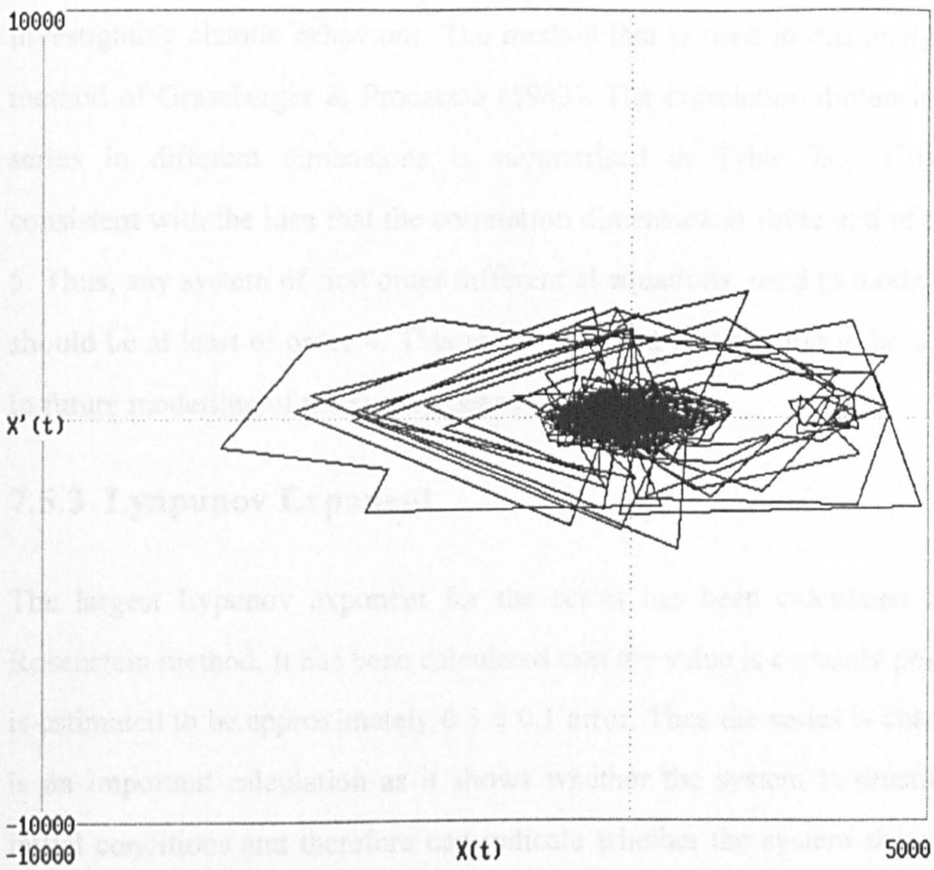

Figure 7-11: **Phase Space of Data**

7.5.2 Correlation Dimension

The correlation dimension is possibly one of the most popular tools in investigating chaotic behaviour. The method that is used in this analysis is the method of Grassberger & Procaccia (1983). The correlation dimension for the series in different dimensions is summarised in Table 7-3. This data is consistent with the idea that the correlation dimension is finite and of order 4 to 5. Thus, any system of first order differential equations, used to model this data should be at least of order 4. This is an important information to be considered in future modelling of the system behaviour.

7.5.3 Lyapunov Exponent

The largest Lypunov exponent for the series has been calculated using the Rosenstein method. It has been calculated that the value is certainly positive and is estimated to be approximately 0.3 ± 0.1 error. Thus the series is chaotic. This is an important calculation as it shows whether the system is sensitive to its initial conditions and therefore can indicate whether the system show signs of chaotic behaviour.

7.5.4 Hurst Exponent

The calculation of Hurst exponent is important because it provides a measure of whether a trend will persist. The Hurst exponent is calculated to be approximately 0.17. This implies anti-persistence in the system, which implies that past events tend to reverse the future. This small value is consistent with the results shown above for a correlation dimension of order 4.

n 1		2		4		8		16		32		
D	CorDim	± error	CorDim	± error	CorDim	± error	CorDim	± error	CorDim	± error	CorDim	± error
2	2.08	0.11	2.157	0.2	2.195	0.14	2.085	0.23	2.085	0.23	2.085	0.54
3	2.929	0.022	3.041	0.015	3.263	0.348	2.991	0.193	2.991	0.193	2.855	0.447
4	3.808	0.041	3.718	0.016	3.617	0.049	3.628	0.072	3.628	0.072	3.403	0.002
5	4.489	0.114	4.606	0.004	4.21	0.049	4.468	0.024	4.455	4.455	4.881	4.881
6	5.035	5.035	5.224	5.224	4.826	0.075	5.127	0.064	5.336	5.336	5.351	0.008
7	5.364	0.051	5.385	0.004	5.39	5.39	5.582	5.582	5.527	0.466	5.921	5.921
8	5.717	5.717	5.734	5.734	5.925	5.925	5.969	0.127	5.636	5.636	5.317	5.317
9	5.991	5.991	5.802	0.224	5.906	5.906	6.074	6.074	6.217	0.434	5.878	5.878
10	5.966	5.996	5.846	5.846	6.232	6.232	6.474	6.474	6.128	6.128	5.933	0.015

Table 7-3: **Correlation Dimension for Detrended Data**

The table shows the correlation dimension for different dimensions *N* and different delays *n*. From the table it can be noticed that the error starts increasing exponentially in dimension 8 for lag 1, dimension 6 for lag 2, dimension 7 for lags 4 and 8, and finally dimension 5 for lags 16 and 32. Thus, considering the minimum dimension for all lags for minimum error, the dimension that can best describe the underlying data set is 4.

7.6 Surrogate Data Test for Temporal Linear Correlations

As mentioned in Chapter 6, at the end of Phase III the surrogate data test is performed in order to increase the validity of the results. For this purpose 39 sets of AFFT surrogates were created and used to re-run Phase III. The results of the surrogate data were then compared with the results of the original data set. In order to reject the hypothesis that the results of the underlying data were subject to temporal linear behaviour, the results of the surrogate data set should be different from the results of the original data. The analysis has shown that the hypothesis of temporal linear correlation should be rejected.

Table 7-4 provides an example of this comparison by summarising the results of the AFFT surrogate data test for dimension four and lag two. According to the table, the correlation dimension of the surrogate data is different from the one of the actual data; the correlation dimension of the surrogate data lies below the correlation dimension of the actual data. Similarly, the Lyapunov exponents of the surrogate data sets are also different (larger) than the one of the raw data. Finally, the Hurst exponent of the surrogate data sets is found to be almost zero, whereas the Hurst exponent of the detrended data is not (it is 0.17).

7.7 Summary

The purpose of this chapter was to answer the fourth research question of this thesis (Section 1.3) and present the results of the data analysis of the underlying case study. The data analysis has shown that there are signs of chaotic behaviour in real time-series of logistics demand. Thus, high-variability in logistics demand can be the result of deterministic behaviour.

	Dimension Correlation	*± error*	*Lyapunov Exponent*	*± error*	*Hurst Exponent*
Raw Data	4.606	0.004	0.214	0.052	0.174
Surrogate 1	4.622	0.13	0.315	0.056	0.003
Surrogate 2	4.567	0.243	0.286	0.057	-0.008
Surrogate 3	4.335	0.095	0.307	0.056	0.002
Surrogate 4	4.578	0.095	0.316	0.056	0.005
Surrogate 5	4.405	0.092	0.296	0.059	-0.003
Surrogate 6	4.49	0.122	0.283	0.057	0.010
Surrogate 7	4.631	0.218	0.282	0.056	-0.001
Surrogate 8	4.628	0.248	0.322	0.056	0.014
Surrogate 9	4.469	0.057	0.339	0.058	-0.018
Surrogate 10	4.406	0.239	0.289	0.054	0.006
Surrogate 11	4.463	0.111	0.32	0.056	-0.014
Surrogate 12	4.577	0.275	0.319	0.057	0.003
Surrogate 13	4.733	0.02	0.295	0.054	-0.009
Surrogate 14	4.305	0.026	0.329	0.056	0.001
Surrogate 15	4.388	0.081	0.32	0.054	0.006
Surrogate 16	4.743	0.257	0.302	0.057	0.008
Surrogate 17	4.226	0.022	0.305	0.67	-0.002
Surrogate 18	4.534	0.044	0.293	0.056	0.009
Surrogate 19	4.525	0.161	0.285	0.053	0.015
Surrogate 20	4.545	0.245	0.322	0.055	-0.007
Surrogate 21	4.284	0.152	0.273	0.049	-0.009
Surrogate 22	4.635	0.157	0.317	0.057	-0.003
Surrogate 23	4.505	0.226	0.309	0.054	0.002
Surrogate 24	4.339	0.012	0.308	0.055	0.003
Surrogate 25	4.686	0.108	0.288	0.059	0.004
Surrogate 26	4.691	0.306	0.304	0.054	0.003
Surrogate 27	4.352	0.012	0.301	0.055	0.000
Surrogate 28	4.877	0.212	0.323	0.056	0.002
Surrogate 29	4.223	4.223	0.295	0.056	-0.005
Surrogate 30	4.454	0.022	0.311	0.058	0.005
Surrogate 31	4.597	0.178	0.318	0.055	-0.009
Surrogate 32	4.543	0.135	0.283	0.058	-0.015
Surrogate 33	4.549	0.015	0.287	0.052	0.022
Surrogate 34	4.643	0.18	0.303	0.05	-0.007
Surrogate 35	5.039	0.452	0.279	0.058	0.002
Surrogate 36	4.72	0.098	0.323	0.057	-0.002
Surrogate 37	4.55	0.318	0.263	0.059	-0.005
Surrogate 38	4.478	0.188	0.305	0.053	-0.001
Surrogate 39	4.622	0.13	0.315	0.056	-0.016

Table 7-4: **Comparison Table of Surrogate Data Results in Phase III**

Thus, the question generated at this point is how the method of CASTS would have been affected if the data was aggregated by two, three or seven days? Would the method of CASTS still provide adequate results? These questions are answered in the next chapter.

Chapter 8

Results (Part II)

Chapter 8:

Results (Part II)

The purpose of this chapter is answer the fourth research question of this thesis by investigating the impact of aggregating the data in different time intervals on the results of CASTS. The structure of this chapter is also based on the method of the CASTS framework and the results are presented in a comparison format. Thus, first, a description of the data is presented, followed by a search for correlations and finally a description of the main characteristics of the data. In the end, a summary of the results is displayed.

8.1 Introduction

Chapter 6 has explained theoretically the construction of a new methodological framework on how to analyse high-level variability in empirical short-time series based on chaos theory. Chapter 7 has applied successfully this method and identified signs of chaotic behaviour in daily-recorded data. Unfortunately, a lot of real logistics demand data is not recorded daily but rather every two, three of seven days. Thus, the question generated is can and how this type of empirically data could be used in CASTS method to test the direct applicability of chaos theory to detect, analyse and anticipate patterns of high-level variability in logistics demands. This chapter deals with the supplementary analysis looking at the original data in different time intervals; two, three days, and five days (weekly). This aggregation corresponds to 316, 210 and 125 data points respectively.

8.1.1 Phase 1: Description of the Data

As in Chapter 7, the first phase of CASTS is involved in looking at the pseudo-state space and the descriptive statistics of the three new aggregated data sets.

Pseudo-State Space

The pseudo-state space plot of the two-day data shows five main dips (Figure 8-1). The peaks do seem not to have many spikes. The three-day data shows a similar structure as the two-day one; however, the peaks are more defined than the two-day one (Figure 8-2). Finally, the weekly data seems to fluctuate without any specific phase pattern (Figure 8-3).

The probability distribution of the two-day data seems to have two different sets of structure (Figure 8-4). Both sets look like normal, Maxwellian, distributions. The probability distribution of the three-day data set also shows two structures, which seem to be almost normal distributions (Figure 8-5). Finally, the weekly probability distribution shows that the first half, low volume orders, gradually increase while second half, high volume orders, gradually decreases (Figure 8-6). To sum up, the two-day, three-day and weekly data set and the probability distribution of both the weekly and the three-day data shows two different types of behaviour.

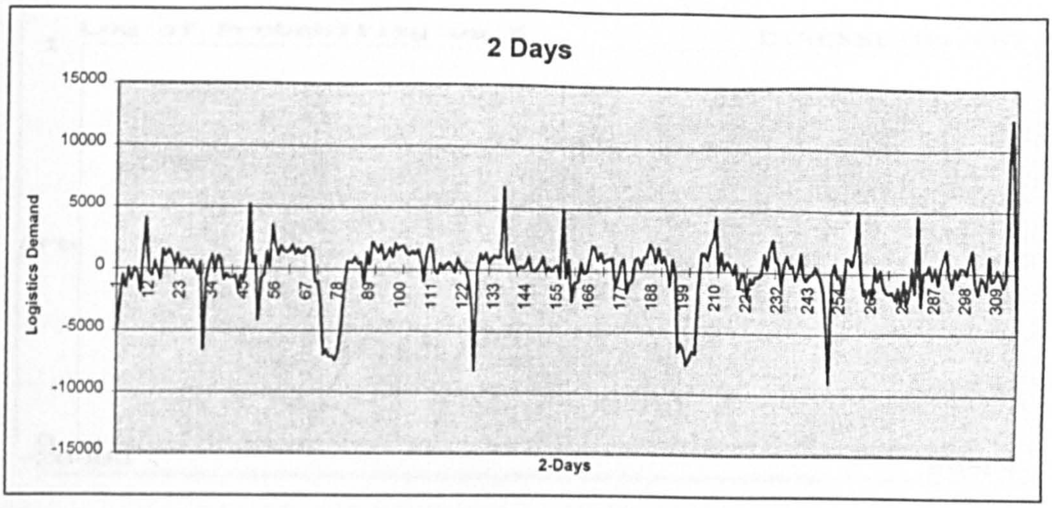

Figure 8-1: **Pseudo-Phase Space Two-Day Data**

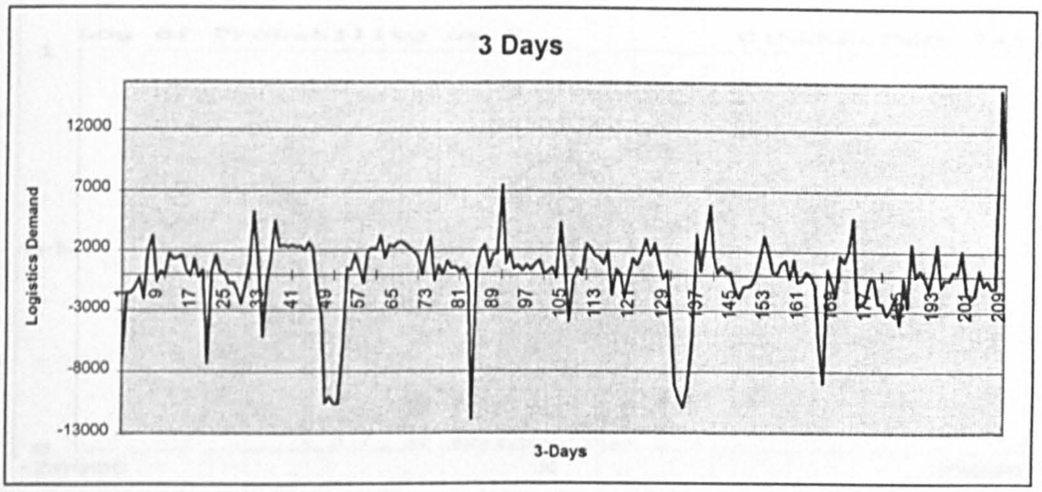

Figure 8-2: **Pseudo-Phase Space of Three-Days Data**

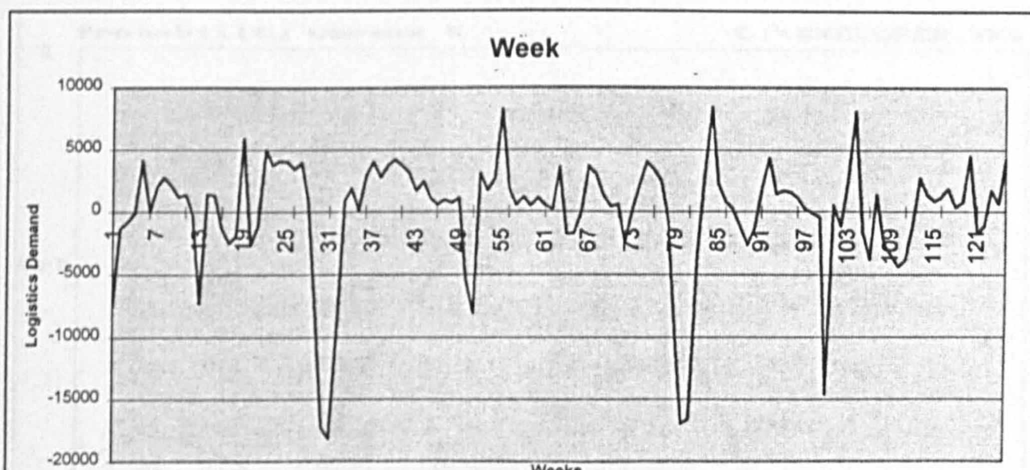

Figure 8-3: **Pseudo-Phase Space of the Weekly Data**

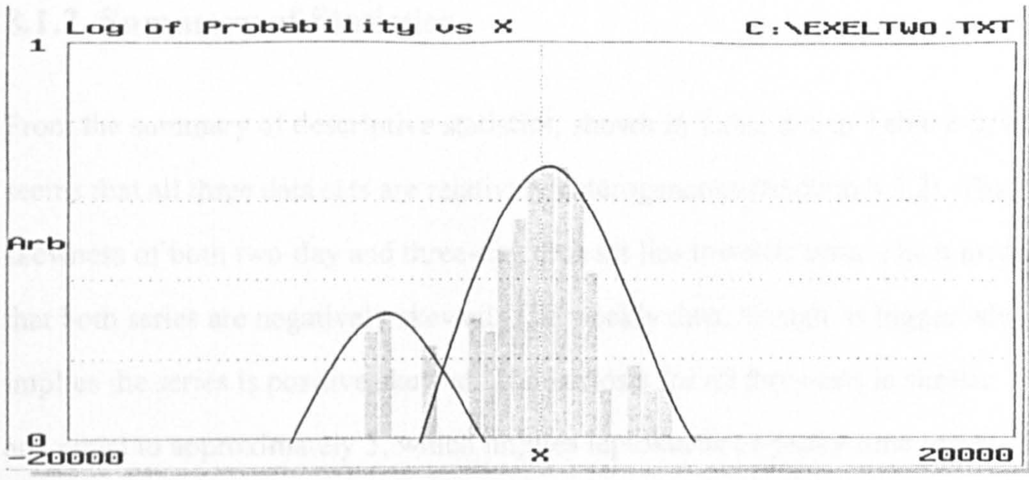

Figure 8-4: **Probability Distribution for Two-Days Data**

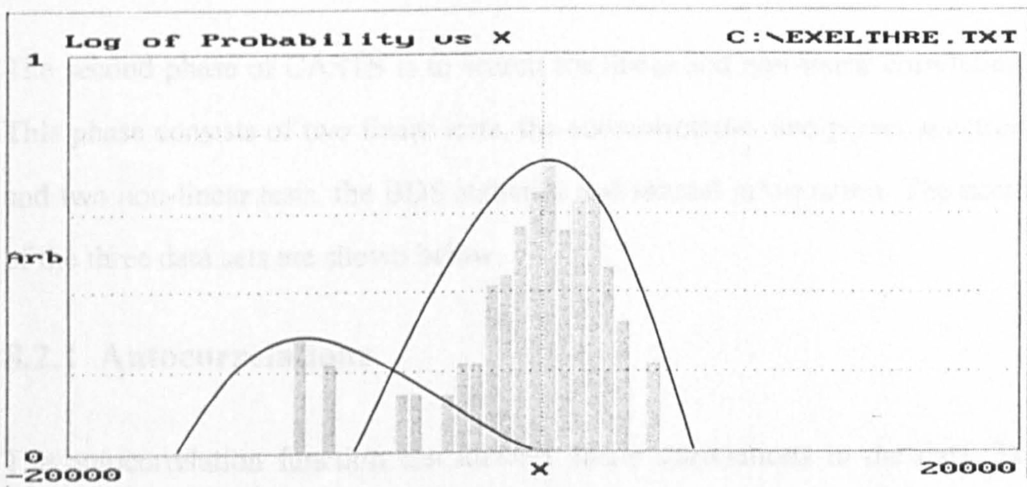

Figure 8-5: **Probability Distribution for Three-Days Data**

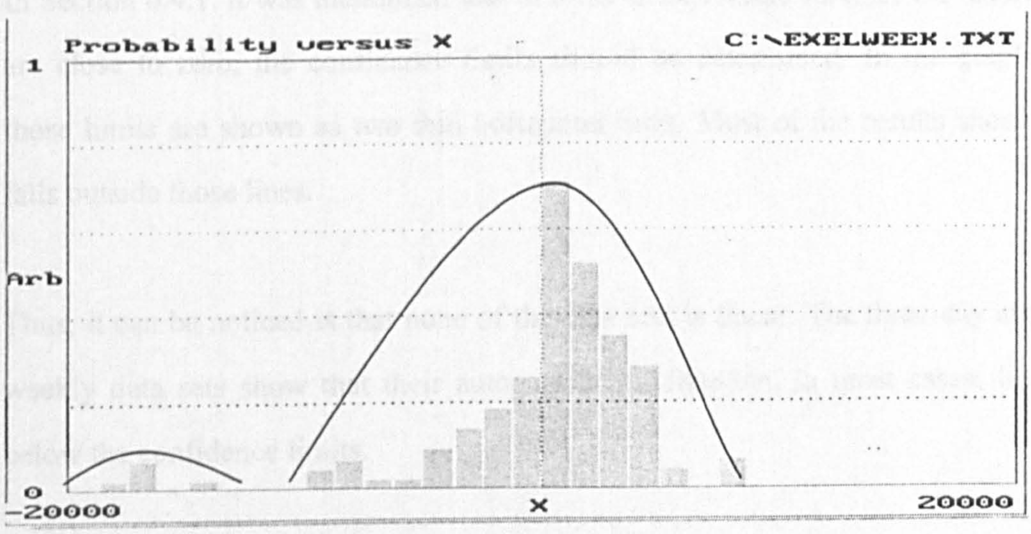

Figure 8-6: **Probability Distribution for Weekly Data**

8.1.2 Summary of Statistics

From the summary of descriptive statistics, shown in Table 8-1 to Table 8-3, it seems that all three data sets are relatively heterogeneous (Section 6.3.2). The skewness of both two-day and three-day data set lies towards zero, which means that both series are negatively skewed. The weekly data, though, is bigger which implies the series is positive skewed. The kurtosis for all three sets is similar and equal to approximately 5, which implies leptokurtic or peaky time series.

8.2 Search for Correlations

The second phase of CASTS is to search for linear and non-linear correlations. This phase consists of two linear tests, the autocorrelation and power spectrum, and two non-linear tests, the BDS statistics and mutual information. The results of the three data sets are shown below.

8.2.1 Autocorrelations

The autocorrelation function can identify linear correlations in the data. The results of the three data sets are shown in Figure 8-7, Figure 8-8 and Figure 8-9. In Section 6.4.1. it was mentioned that in order to determine whether the results are close to zero, the confidence limits should be determined. In the graphs those limits are shown as two thin horizontal lines. Most of the results should falls outside those lines.

Thus, it can be noticed is that none of the data sets is linear. The three-day and weekly data sets show that their autocorrelation function, in most cases, lies below the confidence limits.

Descriptive Statistics

	N	Range	Minimum	Maximum	Mean		Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
V1	316	21551	-9044	12507	1.63	131.66	2340.50	5477943	-.626	.137	5.732	.273
Valid N (listwise)	316											

Table 8-1: **Descriptive Statistics for Two-Days Data**

Descriptive Statistics

	N	Range	Minimum	Maximum	Mean		Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
EXLTHREE	210	27400	-11900	15500	1.09	227.43	3295.74	1.1E+07	-.866	.168	5.206	.334
Valid N (listwise)	210											

Table 8-2: **Descriptive Statistics for Three-Days Data**

Descriptive Statistics

	N	Range	Minimum	Maximum	Mean		Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
V1	125	26589	-18105	8484	.32	416.56	4657.33	2.2E+07	-1.958	.217	5.045	.430
Valid N (listwise)	125											

Table 8-3: **Descriptive Statistics for Weekly Data**

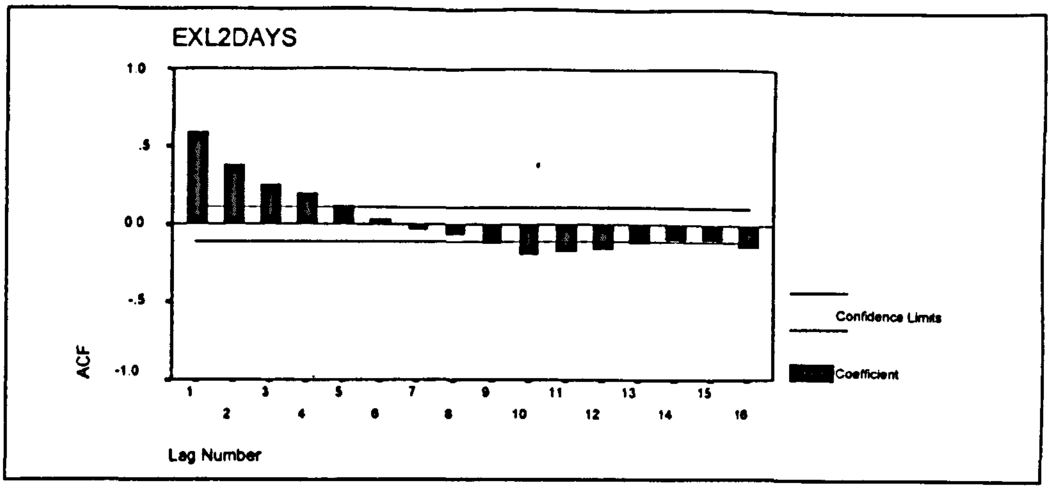

Figure 8-7: **Correlogram for Two-Days Data**

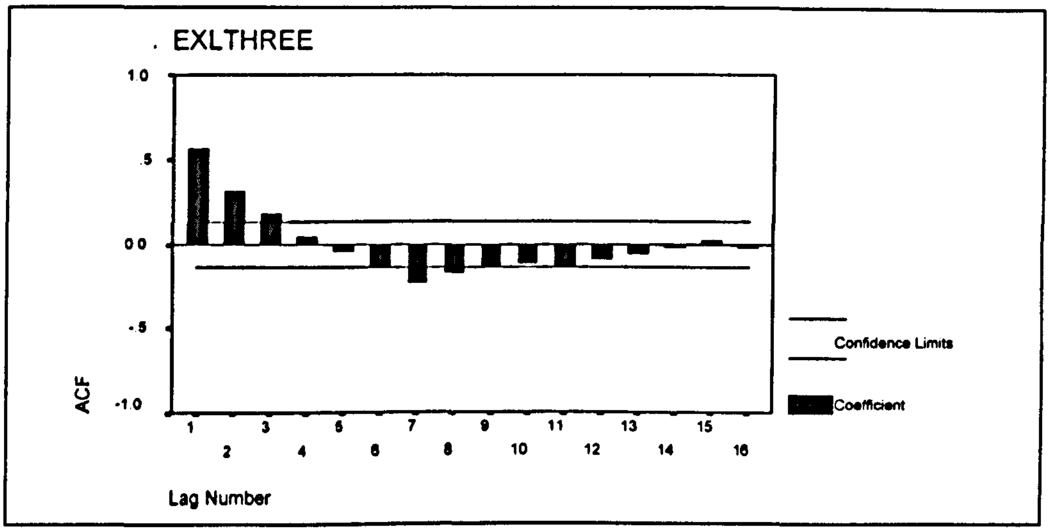

Figure 8-8: **Correlogram for Three-Days Data**

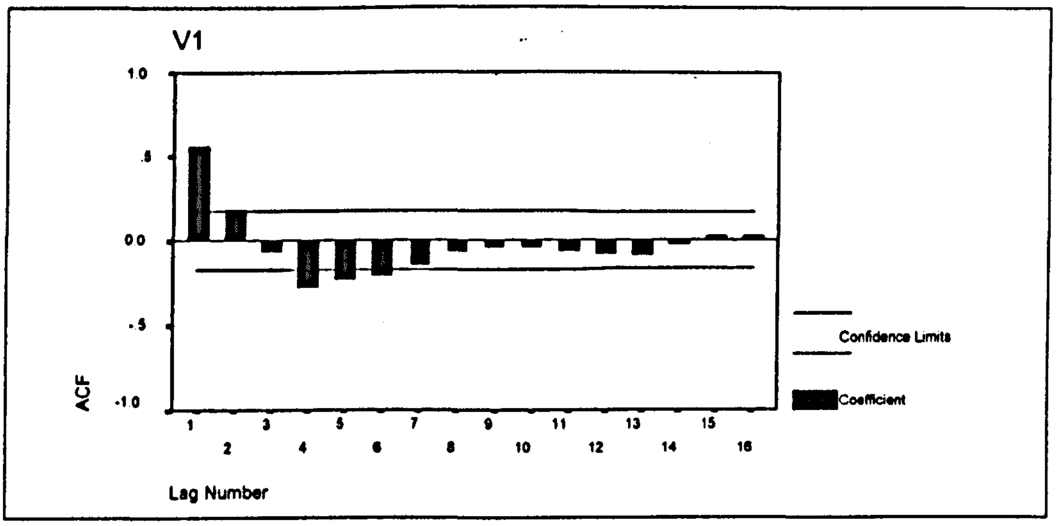

Figure 8-9: **Correlogram for Weekly Data**

In other words, the correlogram points towards random behaviour. The two-day data set shows a correlation that shifts from positive to negative in a gradual pattern. At this stage it cannot be concluded with confidence that the data is random or deterministic and further investigation has to be made.

8.2.2 Power Spectrum

The power spectrum of the two-day data is relatively flat with a tendency to decrease, which is a characteristic of chaotic data (Figure 8-10). The data may be in a high stage of non-linearity. The power spectrums of the other two data sets seem to follow the same trend as the two-day one, however they are relatively more flat, which is characteristic of possible randomness (Figure 8-11 and Figure 8-12). The reason for this slight difference in the power spectrums of the same but differently aggregated data is the fact that aggregation "hides" the daily activity that could be important and have tremendous impact on the overall demand activity.

8.2.3 BDS Statistics Test

The purpose of the BDS statistics is to test the null hypothesis for independent and identically distributed data points. As mentioned in Chapter 7, the BDS test can provide significant results only if it is applied to a data set gretaer than 200 points. Therefore, the test cannot be used on the weekly data, which is 125 points. The results of the other two data sets are shown in Table 8-4 and Table 8-5 and are created by using the CDA software (Sprott & Rowlands, 1995). From the tables it can be safely concluded that the null hypothesis for independent and identical distributed data points is rejected. Thus, knowing this, from the autocorrelation and power spectrum analysis, these data sets are not linear and from here they are not random, then they should be non-linear. Yet, there is one last test in this phase that should be explored.

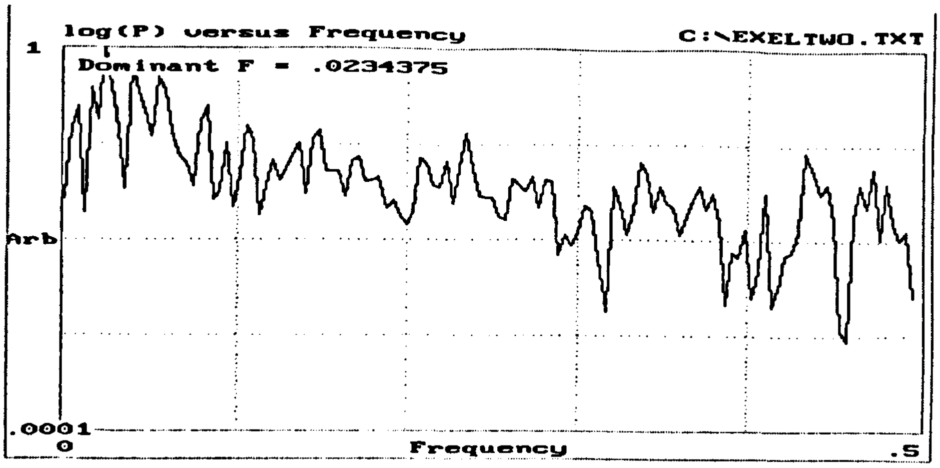

Figure 8-10: Power Spectrum for Two-Day Data

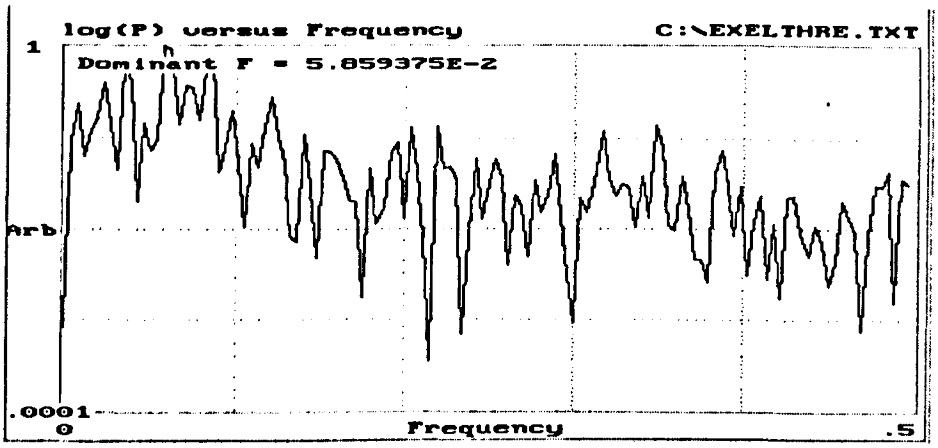

Figure 8-11: Power Spectrum for Three-Day Data

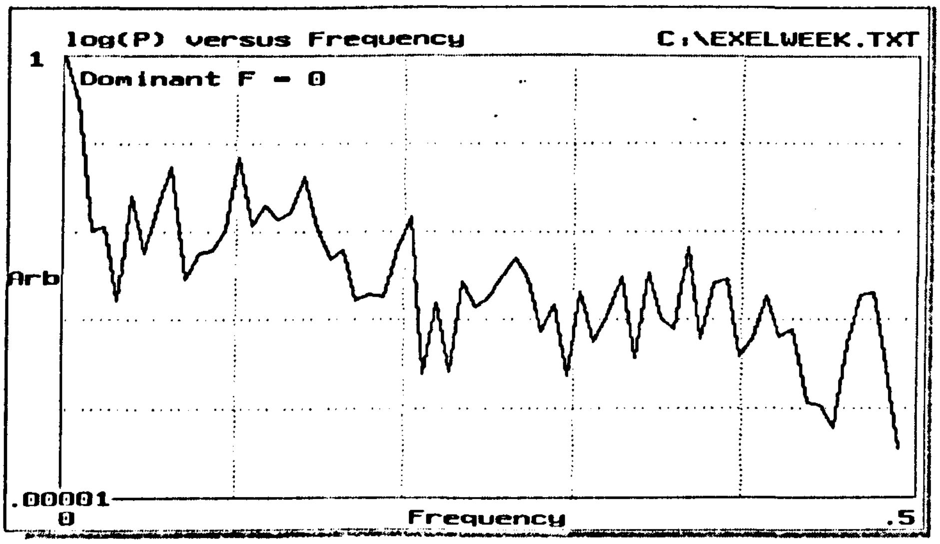

Figure 8-12: Power Spectrum for Weekly Data

N\n	*1*	*2*	*4*	*8*	*16*
2	0.125	0.073	-0.404	-0.449	-0.288
3	-0.124	-0.292	-1.088	-1.202	-0.617
4	-0.331	-0.859	-1.583	-1.837	-1.387
5	-0.486	-1.299	-1.915	-2.097	-1.729
6	-0.481	-1.477	-1.893	-2.088	-1.689
7	-0.417	-1.488	-1.729	-1.924	-1.562
8	-0.337	-1376	-1.529	-1.668	-1.388
9	-0.255	-1.211	-1.283	-1.359	-1.171
10	-0.186	-1.009	-1.044	-1.08	-0.967

Table 8-4: **BDS Statistic for Two-Days Data**

N = embedding dimension, n = delay

D\n	*1*	*2*	*4*	*8*	*16*
2	-0.049	-0.084	-0.290	-0.935	-0.395
3	-0.304	-0.416	-0.787	-1.630	-0.563
4	-0.453	-0.816	-1.338	-2.011	-0.444
5	-0.492	-1.033	-1.540	-2.101	-0.303
6	-0.483	-1.131	-1.570	-2.075	-0.249
7	-0.407	-1.130	-1.467	-1.920	-0.396
8	-0.306	-1.005	-1.256	-1.705	-0.366
9	-0.235	-0.858	-1.006	-1.447	-0.371
10	-0.173	-0.713	-0.795	-1.207	-0.275

Table 8-5: **BDS Statistics of Three-Days Data**

N = embedding dimension, n = delay

8.2.4 Mutual Information Test

The mutual information test looks at the rate information is retained in the system. It is an important test especially for short time series because it can search for general correlations independently of the size of the data set. From the graphs it is apparent that there is some information preserved in the system (Figure 8-13, Figure 8-14 & Figure 8-15). Therefore none of the data sets seems to be purely random. However, the information is not preserved for long times in the systems.

8.3 Characteristics of the System

This section provides more information about the characteristics of the data analysed that can identify possible signs of chaotic behaviour. As in Chapter 7, this section looks at the phase space plots, correlation dimension, Lyapunov and Hurst exponents.

8.3.1 Phase Space

The phase space identifies possible structures in the behaviour of the data. The two-day data, in Figure 8-16, shows a potentially random behaviour in the centre and some orbiting structure (peaks) around that. Unfortunately, the second structure does not seem to have a clear pattern and there are not enough data points available of further analysis. The three-day data, in Figure 8-17, shows a random structure, something that was expected as the probability distribution in Figure 8-5 seemed to be normal. Finally, the weekly phase space, in Figure 8-18, shows similar fuzzy structure as the three-day data set. However, it is noticeable that while most of the activity takes place on the right side of the phase space plot, there are certain high values that drive the system away (left).

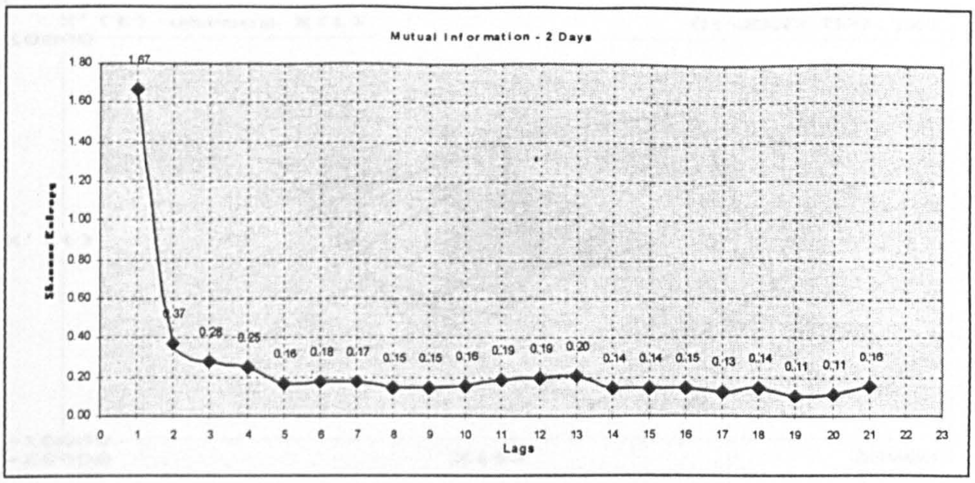

Figure 8-13: **Mutual Information for Two-Days Data**

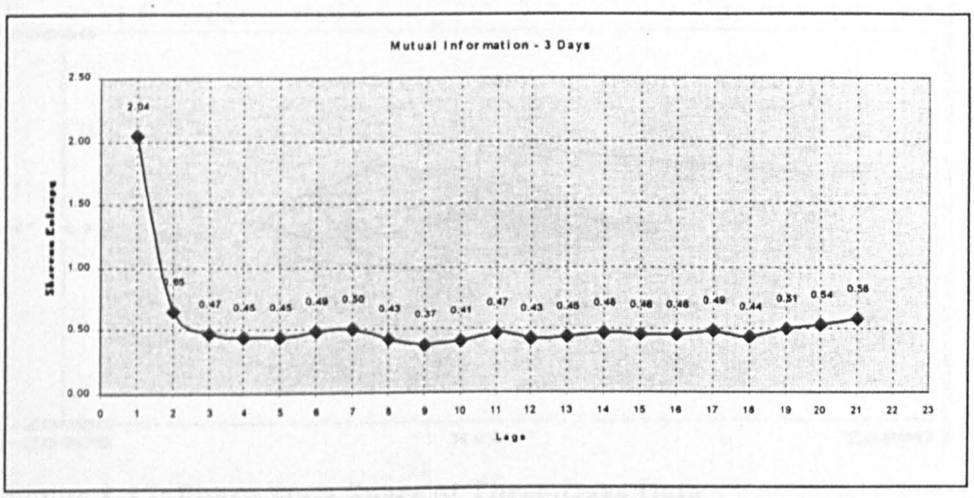

Figure 8-14: **Mutual Information for Three-Days Data**

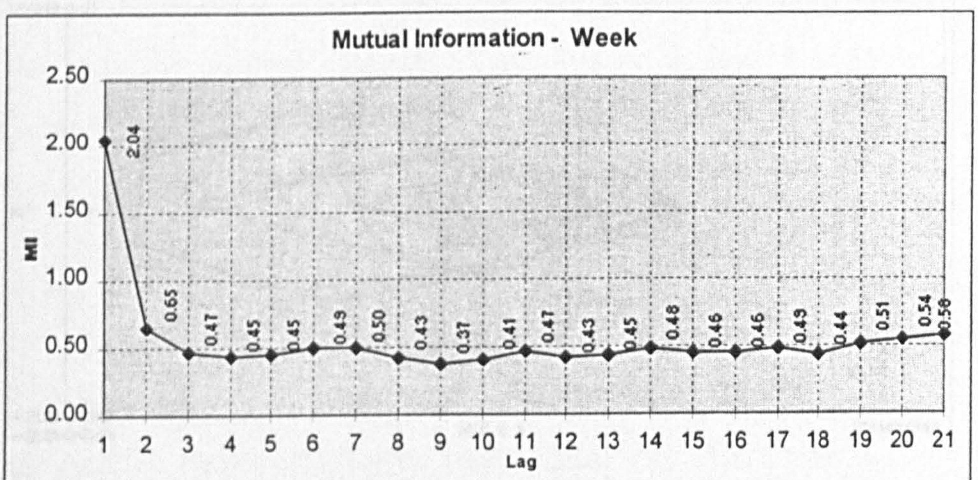

Figure 8-15: **Mutual Information Graph for Weekly Data**

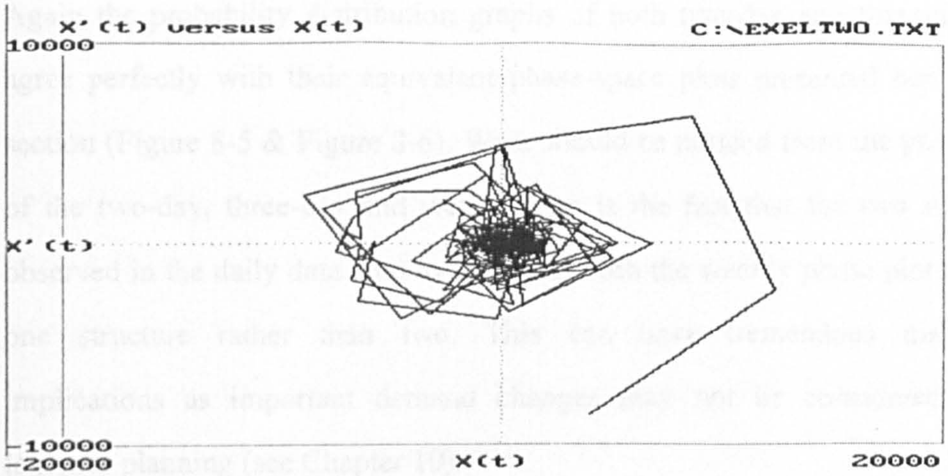

Figure 8-16: **Phase Space State for Two-Days Data**

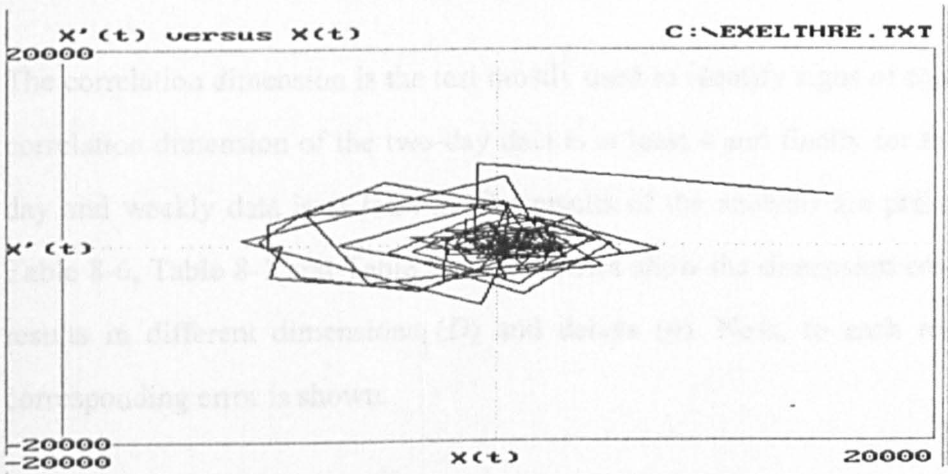

Figure 8-17: **Phase-State Space of Three-Days Data**

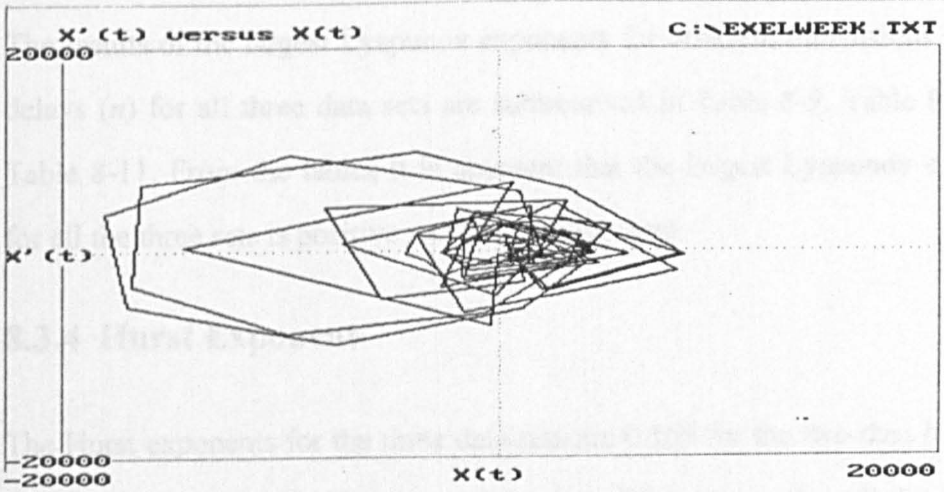

Figure 8-18: **Phase Space State for Weekly Data**

Again the probability distribution graphs of both two-day and three-day data agree perfectly with their equivalent phase-space plots presented here in this section (Figure 8-5 & Figure 8-6). What should be noticed from the phase plots of the two-day, three-day and weekly data is the fact that the two structures observed in the daily data tend to disappear with the weekly phase plot to show one structure rather than two. This can have tremendous managerial implications as important demand changes may not be considered in the logistics planning (see Chapter 10).

8.3.2 Correlation Dimension

The correlation dimension is the test mostly used to identify signs of chaos. The correlation dimension of the two-day data is at least 4 and finally for the three-day and weekly data is at least 5. The results of the analysis are presented in Table 8-6, Table 8-7 and Table 8-8. The tables show the dimension correlation results in different dimensions (*D*) and delays (*n*). Next, to each result the corresponding error is shown.

8.3.3 Lyapunov Exponent

The results of the largest Lyapunov exponents for different dimensions (*D*) and delays (*n*) for all three data sets are summarised in Table 8-9, Table 8-10 and Table 8-11. From the tables it is apparent that the largest Lyapunov exponent for all the three sets is positive and lies towards zero.

8.3.4 Hurst Exponent

The Hurst exponents for the three data sets are 0.165 for the two-day, 0.171 for the three-day and 0.203 for the weekly data. That means that all the sets are subject to anti-persistence.

8.4 Summary

The purpose of this chapter was to investigate the impact on the results of aggregating the data. As it was seen from the analysis the aggregation affected mainly the probability distribution and the phase plots. The rest of the tests produced similar results as with the original data. What has to be mentioned is that by aggregating data certain information about the structure can be lost. Although the two different structures seem not clearly in the probability distribution, as it can be identified in both the original data and the aggregated data, the structure in the aggregated data is not so clear. For example the second peak in the probability distribution function for the weekly data could easily be missed. This of course means that the best results will be obtained by using all the data available and that weekly averages must be viewed with some care.

n	1		2		4		8		16	
D	CorDim	± error	Cor Dim	± error	Cor Dim	± error	CorDim	± error	CorDim	± error
2	1.995	0.379	2.022	0.259	2.197	0.347	2.298	0.379	1.953	0.478
3	2.827	0.343	2.657	0.31	2.874	0.174	3.604	0.72	3.142	0.141
4	3.874	2.59	4.039	0.429	3.685	0.063	3.516	0.316	3.505	0.458
5	4.53	0.09	4.731	4.731	3.906	0.04	4.095	0.282	3.919	1.253
6	4.932	0.534	5.257	5.257	3.778	0.211	3.439	3.439	5.722	5.722
7	4.936	0.353	5.299	0.358	3.624	1.17	5.232	5.232	5.906	5.906
8	4.533	0.074	5.695	5.695	4.383	4.383	5.367	0.165	7.398	3.398
9	5.16	0.577	5.798	5.798	4.426	1.318	5.576	5.576	6.86	6.86
10	4.567	4.567	6.121	6.121	5.568	5.568	6.033	6.033	7.398	7.398

Table 8-6: **Correlation Dimension for Two-Days Data**

n	1		2		4		8	
D	CorDim	± error	CorDim	± error	CorDim	± error	CorDim	± error
1	0.829	0.889	0.748	0.842	0.855	0.892	0.745	0.967
2	2.087	0.32	2.107	0.273	2.072	0.495	1.743	0.37
3	2.967	0.588	2.55	0.383	3.441	0.262	2.814	0.49
4	3.173	0.125	3.366	0.435	3.749	0.728	4.521	0.127
5	3.213	0.412	4.616	6.616	4.497	0.393	5.135	0.048
6	3.786	0.181	4.584	0.96	5.513	5.513	6.348	6.348
7	4.178	0.416	5.13	0.175	5.636	5.636	5.817	5.817
8	4.115	0.231	5.817	5.817	5.509	0.989	6.684	6.648
9	4.752	0.244	5.854	0.285	6.327	1.072	6.44	0.958
10	4.686	4.686	5.924	5.924	6.358	6.358	5.928	5.928

Table 8-7: **Correlation Dimension for Three-Days Data**

n	1		2		4		8	
D	CorDim	± error	CorDim	± error	CorDim	± error	CorDim	± error
1	1.106	0.709	1.1108	0.889	1.133	0.843	3.587	3.274
2	2.076	0.983	2.583	0.815	2.739	1.219	2.968	3.432
3	2.492	0.692	2.973	0.675	3.723	0.266	4.303	3.096
4	3.400	0.669	3.866	1.227	4.996	4.996	4.965	4.965
5	4.667	1.091	3.275	0.662	6.096	6.096	4.965	2.434
6	5.098	1.528	4.316	0.544	6.102	1.297	5.694	1.705
7	4.939	1.985	6.050	6.050	7.398	7.398	4.737	2.661
8	3.525	0.611	6.363	6.363	5.847	5.847	7.398	7.398
9	4.737	0.089	7.398	7.398	5.183	5.183	7.398	7.398
10	4.097	0.108	-	-	4.890	4.890	-	-

Table 8-8: **Correlation Dimension for Weekly Data**

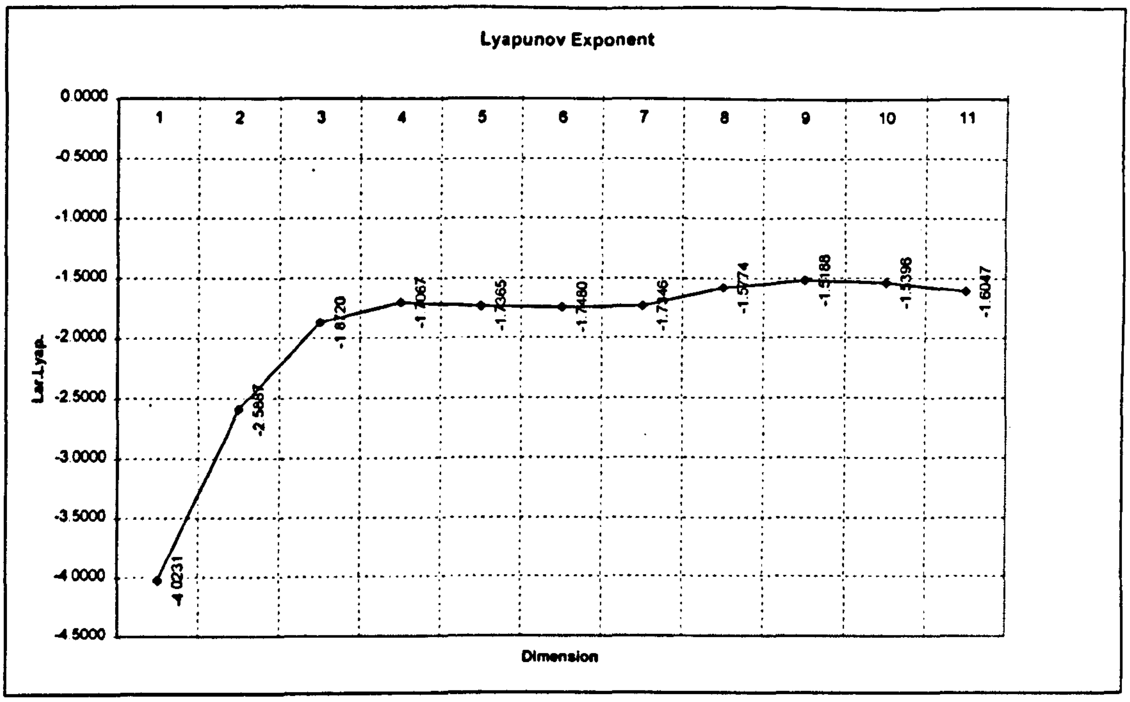

Figure 8-19: Lyapunov Exponent Weekly

n	*1*		*2*		*3*		*4*		*5*		*6*		*7*		*8*		*9*		*10*	
D	lyap	± error	lyap	± error	lyap	± error	lyap	± error	lyap	± error	lyap	± error	lyap	± error	lyap	± error	lyap	± error	lyap	± error
2	1.2	0.191	1.01	0.148	0.75	0.122	0.64	0.109	0.53	0.084	0.39	0.091	0.37	0.083	0.28	0.079	0.25	0.092	-0.23	0.056
3	0.69	-137	0.51	0.115	0.47	0.106	0.43	0.09	0.31	0.086	0.31	0.098	0.23	0.07	0.2	0.071	0.17	0.074	0.172	0.048
4	0.42	0.11	0.36	0.091	0.36	0.092	0.31	0.083	0.26	0.075	0.2	0.065	0.2	0.073	0.17	0.065	0.13	0.053	0.133	0.047
5	0.36	0.092	0.25	0.087	0.23	0.08	0.22	0.084	0.21	0.075	0.16	0.061	0.18	0.052	0.12	0.049	0.1	0.045	0.116	0.048
6	0.28	0.079	0.22	0.076	0.24	0.075	0.17	0.063	0.16	0.061	0.14	0.063	0.15	0.065	0.14	0.043	0.09	0.042	0.081	0.048
7	0.2	0.065	0.17	0.066	0.16	0.061	0.19	0.061	0.16	0.055	0.1	0.055	0.11	0.048	0.1	0.048	0.12	0.047	0.077	0.047
8	0.18	0.059	0.17	0.057	0.13	0.058	0.17	0.06	0.15	0.056	0.11	0.052	0.14	0.056	0.1	0.042	0.14	0.041	0.068	0.043
9	0.19	0.057	0.15	0.056	0.14	0.052	0.14	0.06	0.09	0.044	0.11	0.052	0.11	0.05	0.1	0.046	0.08	0.044	0.074	0.037
10	0.16	0.053	0.12	0.05	0.13	0.052	0.11	0.058	0.1	0.049	0.1	0.048	0.08	0.047	0.09	0.047	0.08	0.046	0.073	0.033

Table 8-9: **Largest Lyapunov Exponent per Dimension for Two-Days Data**

n	1	2	3	4	5	6	7	8	9	10
D										
2	1.325± 0.24	1.082± 0.18	0.812± 0.15	0.569± 0.16	0.569± 0.16	0.520± 0.14	0.338± 0.1	0.300± 0.19	0.266± 0.08	0.263± 0.09
3	0.681± 0.16	0.658± 0.15	0.464± 0.14	0.594± 0.13	0.394± 0.13	0.301± 0.1	0.225± 0.08	0.214± 0.08	0.158± 0.09	0.208± 0.07
4	0.428± 0.14	0.367± 0.11	0.326± 0.11	0.284± 0.12	0.284± 0.12	0.239± 0.08	0.139± 0.07	0.136± 0.07	0.171± 0.06	0.144± 0.06
5	0.384± 0.13	0.250± 0.11	0.292± 0.11	0.232± 0.09	0.232± 0.09	0.238± 0.08	0.159± 0.07	0.126 0.06	0.178± 0.08	0.117± 0.05
6	0.267± 0.11	0.242± 0.11	0.260± 0.11	0.150± 0.08	0.150± 0.08	0.140± 0.08	0.151± 0.07	0.150± 0.08	0.102± 0.06	0.111± 0.05
7	0.203± 0.09	0.196± 0.08	0.205± 0.08	0.146± 0.06	0.146± 0.06	0.159± 0.07	0.131± 0.06	0.128± 0.04	0.071± 0.06	0.097± 0.05
8	0.253± 0.09	0.195± 0.08	0.147± 0.06	0.162± 0.07	0.162± 0.07	0.182± 0.09	0.136± 0.06	0.098± 0.06	0.077± 0.05	0.114± 0.05
9	0.221± 0.08	0.184± 0.08	0.157± 0.07	0.173± 0.07	0.173± 0.07	0.193± 0.08	0.154± 0.07	0.160± 0.06	0.114± 0.07	0.123± 0.06

Table 8-10: **Largest Lyapunov Exponent per Dimension for Three-Day Data**

n	*1*		*2*		*3*		*4*		*5*		*6*		*7*		*8*		*9*		*10*	
D	lyap	± error	lyap	± error	lyap	± error	lyap	± error	lyap	± error	lyap	± error	lyap	± error	lyap	± error	lyap	± error	lyap	± error
2	3.57	0.49	2.01	0.32	1.29	0.28	0.80	0.31	0.54	0.28	0.59	0.15	0.59	0.16	0.49	0.19	0.44	0.11	0.36	0.19
3	1.32	0.30	1.04	0.28	0.72	0.19	0.53	0.19	0.42	0.15	0.35	0.11	0.37	0.11	0.28	0.10	0.28	0.10	0.16	0.07
4	0.78	0.21	0.63	0.22	0.40	0.15	0.29	0.16	0.38	0.11	0.21	0.14	0.29	0.17	0.16	0.11	0.24	0.09	0.14	0.08
5	0.51	0.19	0.42	0.16	0.47	0.16	0.32	0.15	0.25	0.11	0.26	0.16	0.18	0.15	0.15	0.09	0.21	0.104	0.17	0.07
6	0.35	0.15	0.34	0.17	0.31	0.14	0.26	0.15	0.23	0.09	0.19	0.13	0.17	0.15	0.16	0.07	0.18	0.16	0.10	0.06
7	0.41	0.15	0.34	0.14	0.26	0.13	0.27	0.13	0.17	0.17	0.19	0.12	0.17	0.14	0.16	0.08	0.12	0.08	0.12	0.09
8	0.37	0.15	0.34	0.13	0.25	0.11	0.28	0.11	0.19	0.12	0.19	0.09	0.14	0.11	0.16	0.11	0.12	0.09	0.12	0.07
9	0.33	0.12	0.28	0.12	0.22	0.09	0.23	0.11	0.13	0.09	0.18	0.09	0.15	0.11	0.16	0.07	0.12	0.08	0.09	0.08
10	0.21	0.09	0.24	0.11	0.20	0.08	0.17	0.09	0.15	0.09	0.15	0.09	0.12	0.09	0.16	0.06	0.10	0.08	0.08	0.08

Table 8-11: **Largest Lyapunov Exponent per Dimension for Weekly Data**

PART V

DISCUSSION

Chapter 9:

DISCUSSION

Chapter 9

Discussion

Chapter 9: Discussion

This chapter discusses and compares the results obtained in Chapter 7 and Chapter 8. The managerial discussion is included in Chapter 10 and not in this chapter. First, a brief review of the data analysis findings presented in the two previous chapters is given. Then the main observations and conclusions that can be drawn from the data analysis are discussed. Finally, a brief summary of the main issues tackled in this chapter is presented at the end of the chapter.

9.1 Introduction

Chapter 7 discussed the results of the detrended data after applying the method of CASTS. In brief, the analysis has shown that the time series are highly non-linear with strong evidence of chaotic behaviour.

The probability distribution has shown the first indication of the two distinct structures of the data (Section 7.2.2.), while the phase plot has illustrated these structures (Figure 7.11). The everyday demand activities seem to be almost random however they have well defined boundaries within which they act. This structure appears as a fuzzy ball, looking similar to the phase plot presented in Figure 6-7C. The second structure is related to the structure of the behaviour of the increased demand activity. It seems that this structure has a linear pattern (see Figure 6-7 (a)), but there were not enough data points to substantiate this hypothesis at this stage; the phase plot of linear data. However, it is certain that there is a defined pattern in the demand behaviour that could, at a later stage, be accurately estimated and used for anticipation and planning purposes. This can have tremendous managerial implications as the boundaries of each structure of the demand behaviour and the time that the demand has this behaviour can be estimated. In terms of logistics management, the identification of behaviour structures allows a more proactive and more flexible logistics planning as future patterns can be better defined. For instance, inventory levels can be planned to follow the trends of the demand behaviour.

The calculation of the correlation dimension of the data has shown that the best dimension to analyse the series is either the fourth or the fifth dimension. This again has tremendous implications in modelling as it indicates the level of the dimension on which the model should be built. For instance, in the case of the underlying data any investigation or modelling in a lower dimension will suppress the structure of the data whilst in a higher dimension it will distort the data analysis.

The Hurst exponent has indicated that the behaviour of the data shows anti-persistence. That means that past trends do not persist into the future. This has again important managerial implications because it provides important information about the cycles that the data follows. In the case of the underlying data the cycle of the system is two to three days. This is very important especially in forecasting to identify the forecasting period. Any forecasting period lower or higher than this may amplify or suppress the results.

It is seems that the method of CASTS can provide important information about the structure and the future patterns of a time series. However, the next important question raised is how data aggregation affects the results of the CASTS analysis. Such an investigation will help to increase the robustness of the method of CASTS. The analysis presented in Chapter 8 answers this question by looking at the data every two days, three days and weekly. The results of such an investigation will not only explain how over aggregation affects the CASTS analysis but also any other non-linear analysis, since the first two phases are common in any linear or non-linear method. The main observations and conclusions are discussed below.

9.2 Data Aggregation

The aggregation of data can suppress the identification of different structures in the demand behaviour and distort the results of further statistical analysis and forecasting. This thesis proves that by comparing the results that the same analysis gives by looking at the data in different levels of aggregation; daily, tw-days, three-days and weekly. The analysis showed that the probability distribution and phase-space plane are the only tests that show sensitivity to the level of aggregation of the data; the higher the level of aggregation the less accurate the results become (Chapter 7 & Chapter 8). On the other hand, the chaotic analysis in Phase III of the method of CASTS shows low sensitivity to the level of aggregation of the data. It has to be mentioned that some of these tests require a large number of data point to provide accurate results. So, it may be argued that this sensitivity may be the result of the small number of data points. To eliminate this argument, the Surrogate Data Test II was performed in order to support the argument that these tests show much less sensitivity than the probability distribution and phase space, within 95% levels of confidence.

To sum up, the aggregation of the data can suppress important structures can provide vital information in the data structure and future behaviour. It has to be mentioned, the exclusion of data points, such as outliers, will also have the same effect as aggregation. Thus, the over-simplification or the exclusion of tails or certain peaks can severely distort the analysis.

9.3 Strange Structures

As mentioned in the previous section, the probability distribution and phase space are the two tests that are sensitive to the data. The probability distribution although it can identify potential distinct structures in the data cannot provide information on the future patterns of the underlying data behaviour. Phase space on the other hand, can visually represent future patterns and define the boundaries of potential "strange" structures.

The analysis in Chapter 7 and Chapter 8 has shown that there are two distinct types of behaviour in the data; day-to-day fluctuations, which could be random and high dimensional chaos, large scale fluctuations on a longer time scale (every week or so).

The detrended data showed the existence of 20 substantial peaks. Except for the two broad peaks, the remaining peaks involved data over a day or so. It is reasonable to attempt to treat this reduced data set separately from the rest but the fact that less than 20 data points exist in the set raises severe doubts on any statistical analysis. In the probability distribution this is shown as a double normal distribution (Figure 7-4) and in a phase space plot as a doughnut structure orbiting around "everyday" structure (Figure 7-11).

9.4 Data Anticipation

The analysis of Phase III of the method of CASTS besides the investigation of chaotic behaviour, provides valuable information about the structure of the behaviour of the underlying data. The knowledge about the structure of the series can be used for the anticipation of future patterns in the demand. The method of CASTS, using the information of Phase III, becomes the base for future modelling and forecasting.

Further investigation should now focus on modelling the behaviour probably in terms of a small set of non-linear differential or difference equation (e.g. logistics equation). However, this is a non-trivial exercise and best only undertaken after further consultation with the related company to try to put limits on the form of these equations[1].

9.5 Summary

The method of CASTS provides the tools that allow the detection (Phase I), analysis (Phase II) and anticipation (Phase III) of chaotic conditions. The purpose of this chapter was to discuss and compare the results presented in Chapters 7 and 8. The discussion has shown the following:

- There are signs of chaotic behaviour in the logistics demand

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[1] Private communication with Prof. George Rowlands.

- The aggregation of data affects only the probability distribution and phase space.
- Aggregation may suppress certain behaviour which is important to the system
- The method of CASTS can provide information about future patterns in demand behaviour that can contribute to pro-active and flexible logistics planning.
- There is a need for further investigation of the peaks and the two different structures identified.

PART VI

CONCLUSIONS & IMPLICATIONS

Chapter 1O:

CONCLUSIONS &

IMPLICATIONS

Chapter 10

Conclusions & Implications

Chapter 10:
Conclusions & Implications

The purpose of this chapter is to summarise the main conclusions of the study and discuss its implications for both theory and practice. First, a short reminder of how all the chapters are related to each other is given. Then, the conclusions drawn from the investigation of a number of different problems are presented. Next the implications of these conclusions to both theory and practice are discussed followed by a brief discussion of the generalisation of the findings. Finally, a brief summary of the findings is presented at the end of the thesis.

10.1 Introduction

The TPL industry saw exponential growth and increasing importance during the last two decades. As a result, new challenges started to emerge in the industry; the industrial dynamics became more critically important, the need for high logistics flexibility became more eminent, and the creation of new technological advancements created new opportunities. As a result, all these new challenges generated the need for better forecasting methods that could detect, analyse and predict the continuously high-level fluctuations in logistics demand (Chapter 2).

The main reason was identified to be that all the elements and functions of TPL are sensitive to any high fluctuations in logistics demand. Thus, if these fluctuations are not proactively identified, the result would be an impact on the efficiency of TPL operations. The main sources of this high-level variability are seasonal effects, external and internal uncertainty, demand amplification and random effects (Chapter 3). These factors can appear individually or in any combination in the system, impacting on the efficiency of TPL operations in a managerial, operational and financial level. Current research directions seem to focus mainly on reactive approaches to solve the issue of high variability. These can be classified as forecasting integration, demand management, information integration and demand driven or "pull" approach. In addition, forecasting enhancement seems to recycle already in use methods rather than to attempt to explore the potential of other newer methods, which could provide valuable insights into the structure of the correlations of this type of highly fluctuating data (Chapter 3). The above approaches do not seem to provide any adequate information about how to detect, analyse and predict this type of system. The direct application of chaos theory has been used extensively to analyse this type of system in other disciplines (Chapter 4), however, until now the direct application of chaos has not been tested as a potential method to detect, analyse and anticipate high demand variability. At this point it became evident that there was a need to investigate the potential application of chaos theory to detect, analyse and predict high-level variability in the logistics demand of third party logistics (Chapter 1).

The thesis began with a literature review of the fundamental building blocks of the research; elements of third party logistics (Chapter 2), high-level variability in logistics demand (Chapter 3), and chaos theory (Chapter 4). The first review introduced the field of third party logistics, summarised the main issues raised in the field and finally concluded with the main research problem of this thesis; high variability in logistics demand. The discussion continued in more depth in the second review, where the different types of variability are discussed. The review also identified the main sources of high variability in logistics demand, as well as its impact on the effectiveness of TPL operation. In addition, it reviewed and evaluated the current approaches to moderate variability. Finally, the third review introduced chaos theory and explained the main concepts of chaos theory on which the whole research analysis is based.

The thesis then proceeded to the methodological part of the study (Chapter 5). At this stage the author justified how the data collection was made, what the main limitations or issues raised were, and what the mathematical techniques employed to analyse the data were. One case study analysis was employed. The variable investigated was the logistics demand extracted from the EDI files of the company in time-series format. The time scale of the data is over two years.

A framework of data analysis called CASTS (Chaotic Analysis of Short Time Series) was constructed in order to analyse the data (Chapter 6). The CASTS method is a new framework of data analysis directed towards chaotic analysis. It is an amalgamation of linear, non-linear and chaos theory based techniques selected to allow the detection, analysis and possible anticipation of the underlying data set. The CASTS method is composed of the application of BDS statistics, autocorrelation function, power spectrum, mutual information, phase space, correlation dimension, Lyapunov exponent and finally Hurst exponent tests. In addition a surrogate data test is performed in order to achieve a 95% level of confidence in the results.

The thesis then proceeded to the presentation and discussion of the results of the data analysis (Chapter 7, Chapter 8 & Chapter 9). The main conclusions and implications of which are analytically presented below.

10.2 Conclusions about Research Questions & Problem

This section reviews the main conclusions drawn from the analysis undertaken for each research question. Its purpose is to show the contribution of this study to knowledge in both its immediate discipline and its parent disciplines.

10.2.1 Sources of High-Level Variability

What are the sources of high-level variability in logistics demand?

The purpose of the first research question was to understand the nature of high-level variability. The comprehension of the factors that drive demand to fluctuate so much, would provide important information on the potential type of these oscillations and give some hints about the most appropriate method that should be used to detect, analyse and predict their future patterns of behaviour. An extensive literature review on the subject revealed that there was not a comprehensive list of all the factors causing high-level variability in logistics demand. Instead, there were several scattered researches focusing on a single factor, which was mainly investigated to satisfy the purposes of a main research. For instance, seasonality was investigated for statistical purposes to create new statistical tools of analysis, and demand amplification was examined for managerial purposes to show the impact of the bullwhip effect in the supply chain.

The author created a comprehensive list of the most important sources of high-level variability in logistics demand based on an extensive literature review. The study showed that the main sources of high variability are seasonal effects, external and internal uncertainty, demand amplification and randomness (Chapter 3). The main characteristic of these sources is that they are directly and indirectly related, thereby influencing each other. This interrelation results in high variability in the logistics demand, especially in dependent demand such as the logistics demand of the third party logistics.

10.2.2 Impact of High-Level Variability to TPL Operations

> *How are third party logistics operations affected by the high-level variability in logistics demand?*

The purpose of the second research question was to explore the impact of high-level variability to third party logistics operations. The main reason for this investigation was to understand how demand variability affects the efficiency of the main elements and functions of the TPL operations, and use this information to identify what kind of information a forecasting technique should provide. A literature review comprehensive divulged that there was not enough research on this area as such.

The author concluded that there were three levels that high-level variability impacted on TPL operations; the managerial, the operational and the financial level. In the managerial level the impact is reflected on the planning and control, while in the operational level, the impact is reflected on transportation inefficiencies, inventory inefficiencies and longer lead times. Finally, in the financial level the impact is reflected on excess costs.

10.2.3 Methodological Framework

How can empirically obtained short-time series data be used to test the direct applicability of chaos theory analysis in detecting, analysing, and predicting patterns of high - level variability in logistics demand data?

The third research problem was related to the issue of how empirical short time series data can be used to test the efficiency of chaos theory analysis. The purpose of this issue was to construct a framework of analysis that could match the specifications of empirical business data, provide information that could be used in planning and control and would be easy to use for non-experts. The main reason identified was that most of the currently available methods seem to be inadequate to detect, analyse and anticipate high non-linear patterns of behaviour.

Thus, the method of CASTS was constructed. Empirical business data has two main drawbacks. First, it is normally short, less than 900 data points, and has high levels of noise. The method of CASTS considers these issues and suggests the use of a surrogate data test to increase validity in the results. Besides, it is also suggested that certain tests from chaos theory, such as Lyapunov exponent and correlations dimension, that were known to require a lot of data points to provide accurate results, are not so sensitive to the number of data points (Chapter 8 & Chapter 9). The method of CASTS is also constructed in such a way as to provide information about the structure of the data that can be used in logistics planning and control that previous methods were not able to provide (Chapter 3). For instance, the phase space can identify past and future patterns in the logistics demand. From the graph of phase space the magnitude of demand fluctuations along with the time that it takes for them to shift between behaviour, the management can easily create different plans and control methods to manage these demand fluctuations. Finally, the CASTS method is constructed in such a way that it does not require an in depth mathematical background knowledge.

10.2.4 Signs of Chaotic Behaviour in Logistics Demand

Are there any signs of chaotic behaviour in logistics demand?

The purpose of the final research question was to detect signs of chaotic behaviour in highly fluctuating demand. Until now, most of the current research to detect signs of chaos was applied to simulated data (Chapter 3 & Chapter 4). The detection of chaotic behaviour in an empirical data set would provide vital information about the way the actual data behave.

10.3 Conclusions about the Research Problem

The research problem of this thesis was stated in Chapter 1 as follows:

Third party logistics providers operate in an environment where their customers' demands show high levels of fluctuation. Existing methods of analysis and prediction cannot capture these types of fluctuation. Newer methods of analysis and the identification of chaotic conditions have not been tested for applicability to these situations.

The study has successfully investigated the potential relevance of the direct application of chaos theory to detect, analyse and predict high-level variability in the logistics demand of third party logistics. The main contributions of this research were the introduction of chaos theory to logistics research, the construction of the method of CASTS and finally the detection of chaos in real data sets.

Although the direct application of chaos theory has attracted interest and been tested in other fields of management, it has not been the subject of investigation in the specific field of logistics research. This research opens new avenues and gives new directions for further research. In addition, the construction of a new methodological framework of analysis suitable for short-time empirical data sets allows the investigation of the presence of chaos to other data sets. Finally, the detection of chaotic behaviour in an empirical data set gives new direction to further study in how to better manage and control this type of behaviour when it occurs.

10.4 Implications for Theory

Chaos theory is a new discipline in management that opens new avenues of research in logistics management. It unfolds an investigation, which has never been performed before. In addition, the construction of a new methodological framework of analysis, CASTS, not only provides detailed guidelines for the analysis of the detection of highly fluctuating logistics demand, but is also a general methodological outline which any discipline can share in examining short-time scale real data behaviour. The proof is the successful identification of signs of chaos in the underlying data set to a 95% level of confidence. In addition, the CASTS findings showed that the CASTS analysis can be taken further to improve/proceed to more detailed analysis.

Finally, Menzter & Flint support that, "research becomes more rigorous as it adheres more strictly to sound scientific concepts and methods in the development and testing of theories about the issues to be investigated... rigour does not imply use of increasingly sophisticated methodologies just to prove we can use them" (Mentzer & Flint, 1997). This chapter tries to make clear that this research follows the above statement.

10.4.1 Introduction of Chaos Theory in Logistics Research

It is a reasonable speculation that chaos theory is a new and useful paradigm in management. Chaos theory bestows deeper cognition on a system's behaviour. The distinction between other fields dealing with system interactions and chaos theory is that it provides information about how the past affects the future. The past can have an inverted relationship with the future, i.e. whatever happened in the past will never be repeated. In the case that the system reacts positively to a stimulus, then whatever happened in the past might be likely to be repeated in the future. The importance of such knowledge is directly reflected on the way past experiences can affect the future and in using what background information the decision will be made. Knowing how the system is making decisions is an essential prerequisite to effective planning. This is especially so when the system tends to be highly dynamic and prediction cannot give enough accurate information about the future. In this situation qualitative information is essential importance.

As Seake *et al* state:

> *Whether a theory holds or not, knowledge is revealed...a goal of logistics research, as in any research, should be to develop and test*

theoretical systems and statements" (Seaker, Waller & Dunn, 1993: 384).

10.4.2 Construction of New Methodological Framework for Advanced Non-Linear Analysis

Dunn *et al* has stated that,

> *Though the underpinnings of science contain basic assumptions, it must be understood that the importance of science is its ability to provide the following: (1) a consistency in method, (2) exclusion of human values and emotions, and (3) external and internal validity* (Dunn, Seaker, Waller, 1994: 152).

The construction of CASTS is a major contribution to the theory for three main reasons. First, it provides a new analytical tool that gives new insights into the systems' behaviour that could not be captured by traditional methods. For instance, it can pick up slow or hidden changes, identify cycles of behaviour, and define moments of a system's decision to shift from one style of behaviour to another – currently perceived as random incidents. This allows management to make better decisions and be able to keep the system under control avoiding "unintentional disruptions to the limit cycles" (Priesmeyer, & Baik, 1989). Better understanding of the behaviour of the system can allow management to stabilise the system in the long run.

Secondly, it can identify signs of chaotic behaviour in the system. If chaos is present then one must not make the mistake of using linear methods to forecast and therefore to make wrong decisions. Even better if the system proves to be random a stochastic approach might be better. This minimises the chance that management will make wrong decisions that could prove to be fatal

Finally, CASTS can be used as a methodological framework for any other discipline that may be interested in exploring a similar type of behaviour.

10.4.3 Detection of Deterministic Behaviour in Logistics Demand

The identification of signs of chaotic behaviour has tremendous implications for theory. Not only is a new direction of research opening in logistics but also in other disciplines that may have similar issues as in logistics management. This implies that traditional methods of investigation should be updated in such a way as to be able to capture this type of behaviour rather than ignoring it. From this research what can be learnt from the CASTS approach is that it can be further expanded to eliminate its main weakness - the size of the data - and thereby improve the results.

It has to be noted that the reason real time series were chosen instead of simulated data for the analysis, despite their limitations, is very well summarised by Richard Feynman in his quote:

"If it disagrees with experiment it is wrong.
In that simple statement is the key to science.
It does not make any difference how beautiful your guess is.
It does not make any difference how smart you are,
[or] who made the guess...
If it disagrees with experiment it is wrong.
That is all there is to it." (Richard Feynman)

10.5 Managerial Implications

The managerial implications of this research are to improve anticipation, planning and control with the application of the method of CASTS to detect, analyse and anticipate erratic behavioural patterns in logistics demand. The application of CASTS will directly affect all the areas which high-level variability impact (Chapter 2). In other words it will contribute to better inventory turns, better on-time delivery, reduced expedites, improved customer service and reduced cost.

10.5.1 Improve Logistics Prediction

One implication of chaos theory is that random behaviour may be more predictable than was originally thought (Wilding, 1998). The development of chaos theory is the "methodologies that have been designed for a precise scientific evaluation of the presence of chaotic behaviour in mathematical models as in real phenomena. Using these methodologies, it is now possible, in principal, to estimate the "predictability horizon" of a system" (Peitgen, Jürgens & Saupe, 1992: 11). However, "erratic behaviour makes forecasting difficult...chaos theory helps to understand the structure of data, making possible, to prepare forecasts...the theory can be applied to various business and non-business situations" (Priesmeyer & Davis, 1991). In addition, once the technique of chaos theory is learnt it can be applied to other aspects of the company and provide an even better insight into the general system's behaviour. The advantage of this technique is that there is no human interaction error or objectivity issues and still many users can use the method.

10.5.2 Improve Logistics Planning

Poincaré states that there are no solved problems; there are only more-or less solved problems. In any case, chaos theory is the "next management paradigm"

(Stamps, 1997). The theory itself is talking about change and evolution. Logistics managers should learn not to react negatively to the change. Change is not necessarily a negative thing. It just upgrades the system to a different level. It creates new opportunities to be explored.

By standing back for sometime and trying to see objectively the way the demand pattern is emerging we will see that despite the fact that the everyday ordering processes might seem random there is a pattern in it. By using the analytical tools of chaos theory the true pattern that is emerging can be seen. To the question how do you control or encourage the growth of the patterns the answer is you cannot. What the management can do is to create the conditions for these patterns to emerge. In other words, a gradual creation of conditions might be the right timing of targeting a promotion. What is important to be understood by the managers is that experimenting by creating new conditions within your system is not as a risky a task as not to. For instance, "from a competitive strategy viewpoint, the limit cycles of direct competitors may reveal periods of strength and vulnerability" (Priesmeyer & Davis, 1991).

"We need to find processes to engage the whole system in developing its future, creating meaning, creating purpose, creating clarity, about what it is that we are capable of accomplishing as an entity" (Flower, 1993). In other words, possibly all the parts of the supply chain should take part in focusing on the targeting strategy. The real challenge is to get everybody involved in the process. The bottom line is that all parties are going to benefit, learn and grow together in a synergical way.

Finally, "long-term business strategies can only be planned if each business action has a limited number of predictable outcomes" (Lloyd, 1995). As Peter

Drucker suggested, planning is not about predicting the future, but rather dealing with the "futurity of the event" (Drucker, 1985). "Planning requires awareness of the limitations of attempting to assess the future" (Smolowitz, 1996). The method of CASTS provides the tools to obtain all the necessary information needed to create a pro-active flexible logistics planning.

10.5.3 Improve Logistics Control

However, what the third party logistics do not want is

> *The big problem with a compromised decision is it leads to compromised results. A compromised result means you're never managing, you're always reacting* (Cowper, 1998).

If corrective action is delayed then the system will fluctuate (Mass & Senge, 1975). In addition, "Past patterns of system behaviour are never repeated exactly, but may recur within certain limits" (Wilding 1998). Control is not about suppressing chaos. On the contrary, it is about learning as much as possible about the system, quickly recognising possibilities or alternatives, and learning to deal with them; "contemplate changing one's control objectives to suit the system, instead of changing the system to suit one's control objectives" (Chen & Dong, 1998: vii).

There are four internal factors that can influence the behaviour of the system (Preismeyer, & Davis, 1991), and consequently control its behaviour. These are the firm's structural characteristics and scaling capacity, differences in limit cycles with the other co-operating firms decisions made by the management, and finally the size of the firm.

10.6 Limitations

Two limitations were identified during this research. Both of them are related to data collection issues. Most of the TPL companies do not keep records for more than two-and-a-half to three years. The main reason is the storage of the data. Even those that do, have their records either kept in a written form or in an older computing system that it is not compatible with the currently used one. The second limitation concerns the recording policy that each company uses to input orders into their system. Some companies record the orders on a daily basis as they come into the company. In this case, there may be a sufficient number of data points to perform a valid data analysis. However, some other companies record their orders on a weekly basis. Such cases produce small data sets for which the validity of the analysis and results may be under criticism. Thus, even access to three years of data may not prove to be enough for a good analysis.

10.7 Generalisability

At this point it is necessary to clarify which findings can and which ones cannot, be generalised from this thesis. The fact that signs of chaotic behaviour were found in one real data set of logistics demand, permit the generalisation that high-level variability in logistics demand can be deterministic in nature and therefore subject to chaotic behaviour. However, not all logistics demand sets experiencing high-level variability are chaotic. It is advisable that in order to classify a system as chaotic the method of CASTS should be applied.

10.8 Implications for Further Research

There are three directions for further research. The first direction emanates from the issue of generalisability. The research followed a case study methodology. Therefore, there is a need for a survey research to generalise the findings. In addition, the same research can be applied to several other logistics data sets in the same third party logistics operations (e.g. inventory quantities) in order to investigate potential commonalities or differences in their patterns of behaviour.

Last but not least, the final direction, which is related to the data limitations, is to lead further research towards modelling of the system, and to use the model to explore such problems as control and possibly prediction. In other words, to complete the CASTS method to detect, analyse and predict high-level fluctuations.

10.9 Summary

The purpose of this thesis was to investigate the fundamental insights emanating from the direct application of chaos theory to explore the nature and structure of high-level variability in the logistics demand of third party logistics. The research was directed towards the detection of signs of chaotic behaviour.

The thesis first investigated the field of third party logistics, identified the main issues in the field and selected the issue of high variability in logistics demand as the main research problem of this thesis. The analysis continued by recognising the areas of TPL operations which high variability in logistics demand impacts. The sources of these intense fluctuations were also identified and discussed. Furthermore, the study reviewed and criticised the current approaches to moderate variability by exposing the necessity to further investigate the direct application of chaos theory to detect, analyse and anticipate this type of behaviour. As a consequence, the analysis continued with a review of chaos theory, which was accompanied by an explanation of the main concepts of chaos on which the whole research analysis is based. Thus, the need for the construction of a new methodological framework became apparent. At this stage, the author proposed the method of CASTS. The research methodology of the study and a full explanation of the construction of the CASTS method were therefore presented. The method of CASTS was tested on an empirical logistics data set. The analysis has shown that there were signs of chaotic behaviour in the patterns of the data and the method of CASTS could efficiently provide this result to within 95% levels of confidence. The main finding of this research can be summarised as:

High-level variability in logistics demand was proven to be chaotic, in the case example.

This finding has a twofold importance. First, it verifies that chaotic behaviour does exist in real demand systems, and second validates application of the method of CASTS to analyse this type of data. The method of CASTS can be further explored in trying to either develop it as a new philosophy of data analysis that leads to scenario building depending on the different types of behaviour that can be observed or, incorporated into an already established forecasting philosophy, which lucks a chaotic time series data analysis method. In this, way it can be safely be concluded that chaos theory can improve the third party logistics planning and control and potential anticipation.

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& MATLAB CODE

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PHASE SPACE FOR AFFT

SURROGATE DATA

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CASTS' COMPARISON RESULTS

Appendix 1
Case Study

Ford Motor Background

Ford Motor Company was established by Henry Ford in 1903 and has managed to stay the UK car market leader for 25 consecutive years. Currently it is the 2nd largest international trader with over $6.5bn in freight costs. The freight in transit at any time constitutes up to 500,000 tons, utilising a multimode form of transport. Ford deals with almost 4000 suppliers, 31 powertrain plants, 54 assembly plants, 13 stamping plants, 20,000 dealers in 200 countries (Hoffman, 2000) and 51 third party logistics providers.

In order to co-ordinate this complicated supply chain, Ford focus on maintaining good relationships with its suppliers (Austin, 1999). There was a conscious decision in early 90s to reduce the number of its suppliers and focus on more long-term contracts with them. Ford supported its suppliers to improve their operations, in exchange for price reductions, with a range of techniques, such as JIT, TQM, and statistical process control. Also, in 1995, Ford Motor Company undertook a major restructuring plan in an attempt to reduce costs, the so-called Ford 2000. The aim of this plan was to incorporate all the Ford Motor business in the world into a single global organisation. This attempt required the initiation of a common operational process, such as Order-to-Delivery (OTD) and the Ford Production System (FPS). The purpose of OTD is to start the production of a car after the order has come into the dealers' system. The maximum time for the production of a vehicle would be 15 days. After the order is accepted, Ford's operational system would be informed. Ford's operational system follows the FPS system. The purpose of which is to allow a more efficient and lean flow of information and material within the supply chain. The notion of this system is that Ford can inform its supplier days in advance on what and how many spare parts it needs. In this way a collaborative forecasting efficiency could be achieved. As a result, information flow was enabled to be available simultaneously in all of Ford's operations around the world. The IT capabilities of Ford have not stopped there. Later Ford introduced the use of intranet and extranet, the application of B2B concept and Ford Retail Network (FRN). The company even proposed the establishment of an Automotive Network exchange with Chrysler and General Motors that allowed more product information collaboration.

Exel Logistics Background

Exel Logistics started in 1982 as Britain's National Freight Company Ltd., which was later sold to its employees and became the National Freight Consortium (NFC). After that, and through some merges, the Exel Logistics brand was launched in the U.K in 1999 with the goal of building a global logistics business.

The automotive sector counts for 7% of the company's business (Figure 1). There are three main services that Exel Logistics provides to the automotive market. Those are inbound to manufacture, service and replacement parts, and vehicle management services. The inbound to manufacturing service includes sub-services, such as the management of imports and exports, collection planning and management, supplier park final configuration services (e.g. sequencing and sub-assembly), and plant services (e.g. line-feeding). The service and replacement parts service include sub-services such as international freight forwarding, container management, inventory management, procurement, distribution centres' services, and outbound delivery services. Finally, the examples of vehicle management services cover finished vehicle support services, operational services, marketing services, distribution services, and pre-production services (e.g. benchmarking, procurement and disposal).

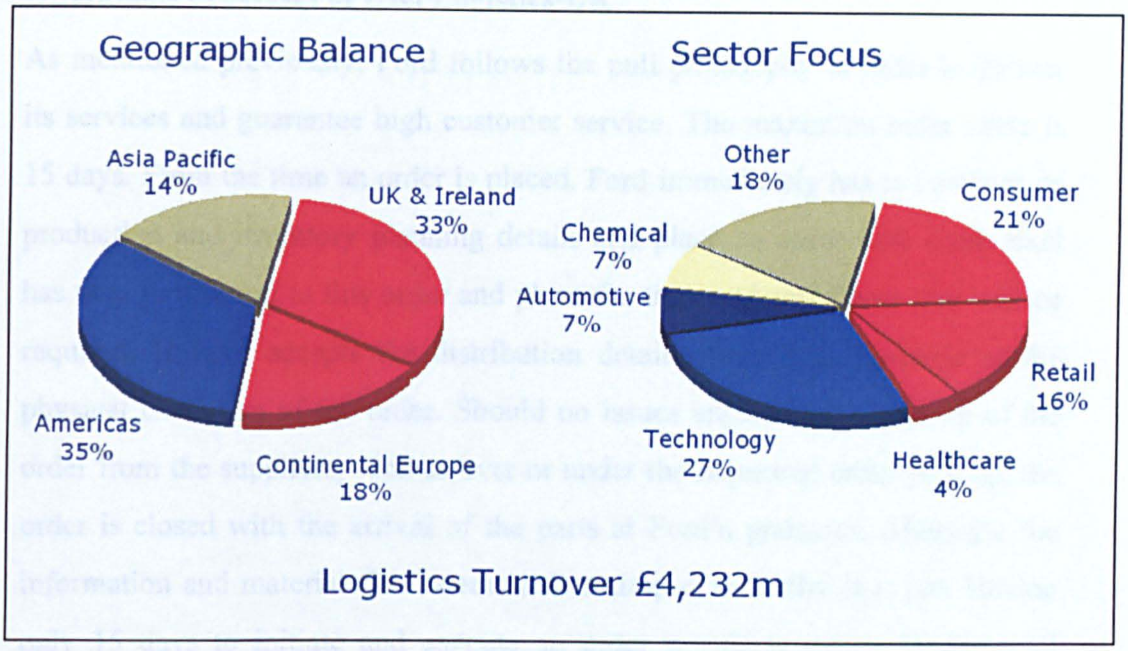


Figure 1: Exel Profile

Source: Exel Logistics (2002), http://www.exel.com/company/keyfacts.asp
More information about the company can be found at the above internet site.

Also, Exel has established three service divisions to meet more specialist requirements. Those are the Automotive Management Services, Wheel and Tyre Services, and the Integrated Collection Service.

Exel Logistics & The Ford Motors Company in the UK

Exel Logistics has a long-term contract with Ford. Exel is responsible to plan, consolidate and move all the material/spare parts from the hundreds of suppliers to the Ford manufacturing plants. In order for Exel to achieve that, it has to act as the data manager, translating material releases to the optimum logistics network to best service the needs of several European plants.

Exel serves three main manufacturers in UK. Those are Rover, Toyota, and Ford. Each company has an exclusive long-term contract with Exel. However, depending on the needs of the specific companies, different policies are applied to serve the customer better.

Operations Processes of Exel Logistics-UK

As mentioned previously, Ford follows the pull philosophy in order to deliver its services and guarantee high customer service. The maximum order cycle is 15 days. From the time an order is placed, Ford immediately has to consider its production and inventory planning details and place an order with Exel. Exel has then to respond to this order and place the time and cost frame that will be required. If Ford accepts the distribution details, then Exel proceeds to the physical execution of the order. Should no issues appear at the pick up of the order from the suppliers, such as over or under the requested order pick up, the order is closed with the arrival of the parts at Ford's premises. Although, the information and material flow seems rather simple, in reality it is not. Having only 15 days to initiate and execute an order translates into a fundamental challenge for Exel; to plan a logistics system, which responds well to last minute orders, but maintains low costs and high operational efficiency. It is a similar problem with safety stock levels and inventory. What is the breakeven point for balancing flexibility and low cost?

Currently, Exel Logistics responds to this issue through a generic pull system (Figure 2) and integrated operational planning (Figure 3). The generic pull system of Exel is set in four main phases; the strategic plan, validation phase, counter-measure and finally the operational plan. The strategic plan is reviewed monthly and is the basis for the logistics operations. Every time an order comes in, it is checked against the predetermined logistics framework to make sure that it can be delivered. In the presence of last minute problems, i.e from the orders coming in, the operational team is responsible to solve them. Also, the operational team defines the changes and, whenever necessary, informs the strategic plan of any major changes that may need to be done. The operational team has the responsibility to examine the logistics demand patterns and translate the issues into floor decisions with meetings taking place everyday.

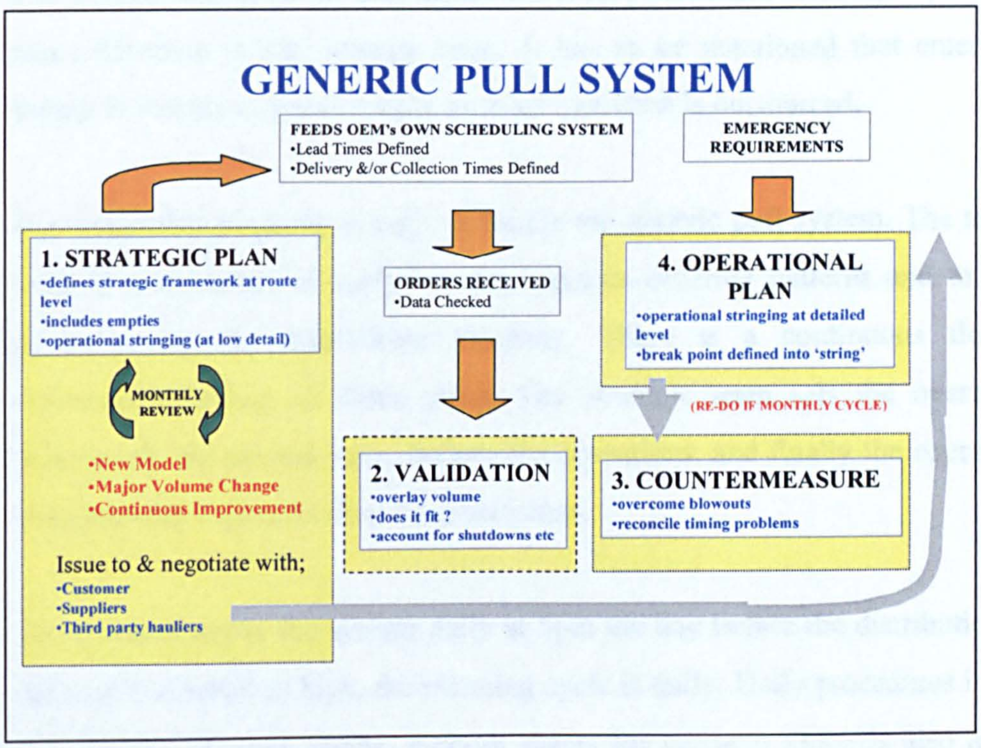


Figure 2: Operational Decision Processes
Source: Exel Logistics Archives (1999).

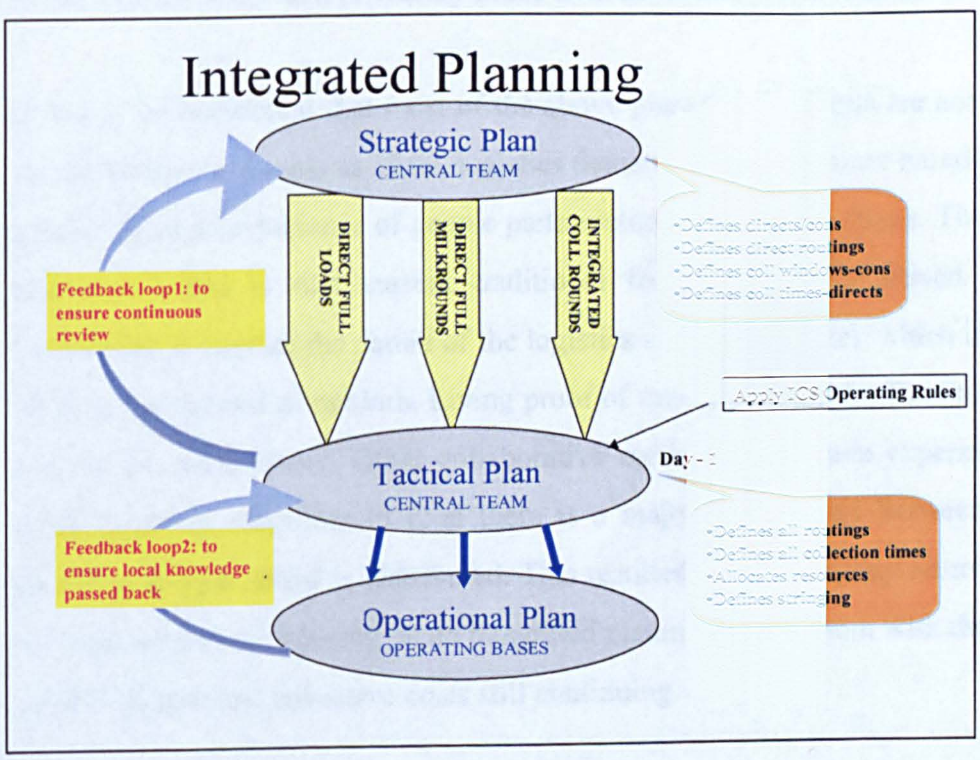


Figure 3: Exel Integrated Planning Procedures
Source: Exel Logistics (1999)

The operational decision and information loop is closed with the operational team reporting to the strategy team. It has to be mentioned that emergency transport that Exel cannot satisfy with its own fleet is outsourced.

The integrated planning is built to satisfy the generic pull system. The tactical team is responsible in analysing the logistics ordering patterns and to make decisions on the distribution planning. There is a continuous flow of information among all three plans. The strategic team sets the operational framework, the tactical team designs the operations, and finally the operational team translates them to shop floor decisions.

The demand enters the system daily at 5pm the day before the distribution. As demand variability is high, the planning cycle is daily. Daily procedures include the creation of route sheets, pick-up sheets for carriers. There is also a daily check up on potential discrepancies between pick-up sheets and material availability in order to ensure high customer service. Optimisation of the routing network takes place in a bi-weekly bases with the release of a data file.

It has to be mentioned that most of the above planning decisions are not based on the forecasting analysis of the logistics demand. They are rather based on the knowledge and experience of people participating on the three teams. The main reason for this is that current traditional forecasting tools proved to be inadequate to capture the nature of the logistics demand for Exel, which in most cases is interpreted as random. Living proof of this is the need for Exel to adopt a daily planning policy. Other collaborative methods have been experimented with, however according to Exel there is a major discrepancy between what should and what actual is distributed. This resulted in the company returning to its original plan of focusing on an integrated planning pull system with the issue of inefficiency and excessive costs still continuing.

The Challenge

To sum up the above discussion, the main challenge that Exel faces can be summarised as:

> *How can Exel Logistics improve forecasting and minimise the demand variability in order to improve efficiency and reduce costs of its logistics operations?*

The propositions for this challenge are the following:

- There is high daily variability on the logistics demand
- Currently available methods of forecasting do not provide efficient results
- The strategic and operational planning is solely based on the executive experience rather than on analysed data
- The order cycle of each order is very short, less than 48 hours
- The operational efficiency of the logistics processes needs to be improved

Proposed Solution Based on Thesis Results

The above discussion has proven that Exel lacks the right data analysis tools to explore their demand patterns and make efficient decisions. The analysis of this thesis has shown that the Exel's demand has elements of chaotic behaviour. For that reason current traditional data analysis tools cannot provide efficient results. Exel is currently depending on casual methods of forecasting, which cannot guarantee high levels of accuracy. For that reason the adaptation of a forecasting methodology that can capture the dynamics of Exel's demand variability and can provide good insights on the patterns of demand behaviour is recommended. This thesis is focused on developing such a method, which will be suitable for similar situations. The method of CASTS can capture chaotic behaviour and provide valuable information that can improve forecasting and minimise demand uncertainty. The following steps can apply the method of CASTS:

1. Incorporate CASTS to their forecasting system
2. Based on the result of CASTS create different scenarios of demand behaviour
3. Based on this create different logistics plans to defend demand changes
4. Incorporate those results to their strategic and operational planning

Appendix 2:

Commentary on C & Matlab Code

```
/* C-code to accumulate the individual entries in the EDI
files into *//* seperate days. *//* Peter Boyle, 2001 */



#include <stdlib.h>         /* Header files - contain all
C-code */#include <stdio.h>       /* standard libraries,
standard */#include <math.h>          /* input/output and
maths functions */

main ( int argc , char **argv ) /* Main function call*/

{FILE *fptr1, *fptr2;/* Initialise variables and pointers
*/long ACcode;long nxtAC;long QTY;long nxtQTY;

/* Instructions on how to use code */if ( argc != 2 )

{printf("Usage: %s <file1> <file2>\n",argv[0]);exit(0);}

/* Open file containing raw data */
if ( (fptr1 = fopen(argv[1],"r")) == NULL ){
perror("Couldn't open file1");
exit(0);}

nxtAC=-1;

while ( 1 ) {/* Read code from file 1 */
load_line( fptr1,&ACcode,&QTY,&nxtAC,&nxtQTY);
printf("%ld %ld \n",ACcode,QTY,nxtAC,nxtQTY);}


}/* Function to load individual lines of data */
void load_line ( FILE *fp, long *code, long * qty, long
*ncode, long *nqty)

{long tcode,tqty; /* Initialise the local variables  */
long firstcall;char numstr[80]; *qty = 0; /* Zero the
current QTY */
```

```
/*If next line already loaded (i.e. not first call to
this)*/

if ( *ncode > 0 ){tcode = *ncode; /* Set variable "tcode"
to be equal to */tqty  = *nqty; /* raw data "*ncode"
*/firstcall = 0;}

else if ( *ncode == -3 ){  /* Check for end-of-file */
fprintf(stderr,"End of file\n");
exit(0);}

else {/* Set "tqty" equal to zero  - do this  */
tqty = 0;/* in first call to function */
tcode = *ncode;firstcall = 1;}

do {/*Load the next line*/ if ( fscanf ( fp, "%s %s
%ld\n", numstr,&dd,&mm,&yy,nqty ) != 2 ) {
*ncode = -3;*nqty = 0;}

else{*ncode = strtol(numstr,NULL,10);}

if ( (tcode == *ncode)  || firstcall) {firstcall = 0;
tqty += *nqty;  /* Sum up the logistics demand for */
tcode = *ncode;n  /* individual days  */}

} while ( tcode == *ncode );

*code = tcode;
*qty = tqty;}

/* End of Program */
```

Bifurcation Diagram

```
%%% Initialise variables  %%%
rs = 1;
rn = 4;
to = 900;
n = 10000;
s = 1:n;
snum = to:n;
x(1) = 0.5;

hold                     % Hold graphics window open
                         % (for multiple plots on one graph)


%%% Code to calculate logistics equation              %%%
%%% For every "r" value, calculate 10,000 "x" values  %%%

for r = rs:0.01:rn,          % Main loop, incrementing "r'
from
                         % 1 to 4 in stepd og 0.01
   count = 0;
   counter = 0;              % Initialise variables
   num = 0;

   for t = 1:n,              %   Loop   to   calculate   "n"
"x(t+1)"s for every "r"
          count = count + 1;
          dummy(counter+t) = r;
          x(t+1) = r.*x(t).*(1-x(t));
          xx(count) = x(t+1);
   end

   for i = to:n,        % Set variables to be plotted
          num = num +1;
          dumplot(num) = dummy(i);
          xplot(num) = xx(i);
   end
```

```
   plot(dumplot,xplot,'y.') % Plot all "x" values for each
"r"

end % Return to start of main loop and increment "r"

title 'Bifurcation Diagram' % Add legends to graph
xlabel 'r'
ylabel 'x[t]'
```

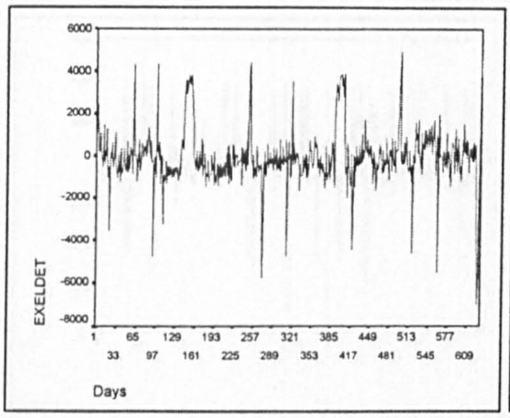
Initial Conditions Diagram

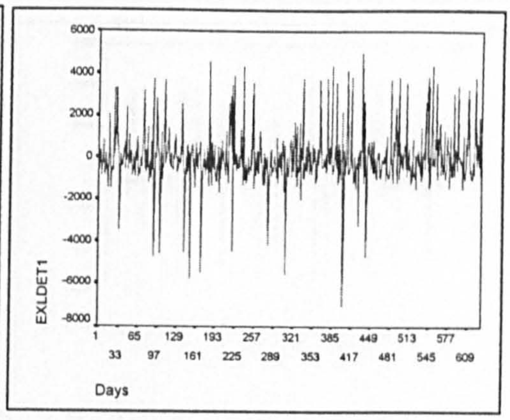
```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%
%%% Matlab code to draw different representations of the
Logistics Equation %%%
%%% Note difference initial conditions x1 = 0.3, x2 =
0.30000001 %%%
%%% Figure 1: Phase Space Plot %%%
%%% Figure 2: Graph of Logistics Equation %%%
%%% Figure 3: Sensitivity to Initial Conditions %%%
%%% Figure 4: A different plot of the Sensitivty to
Initial Conditions %%%
%%% Figure 5: A different plot of the Sensitivty to
Initial Conditions %%%
%%%%%%
%%% Paul McNamara, 2000 %%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%
clear all % Reset all variables

r1 = 3.99; % Value of 'r' in the logistics equation
r2 = 3.99; % Value of 'r' in the logistics equation
n = 50; % Number of data points
x1(1) = 0.3; % Initial Value of Red Trace
x2(1) = 0.30000001;% Initial Value of Blue Trace
ween = 25; % For later graphs : Graph 1 = "1 to ween",
Graph 2 = "ween to n"
rs = 1:n; % Array rs = 1 to n (i.e
1,2,3,4,5,6,7......49,50)
hold % For graphics, so that each pont is drawn on old
graph (hold current graph)
for t = 1:n-1, % FOR loop to calculate time series of
logistics equation
x1(t+1) = r1.*x1(t).*(1-x1(t)); % Logistics Equation for
x1
x2(t+1) = r2.*x2(t).*(1-x2(t)); % Logistics Equation for
x2
plot(x1(t+1),x1(t),'w*') % Graph the data (differential of
x (i.e. dx/dt) against x)
end % End of FOR loop

set(gca,'fontname','Arial','fontsize',16)  % Set font size
and name
title 'Phase Space Plot'            % Put title on graph
xlabel 'x[t]'                       % Put label on x-axis
ylabel 'dx[t]/dt'                   % Put label on y-axis

figure  % Create new window for next graph
```

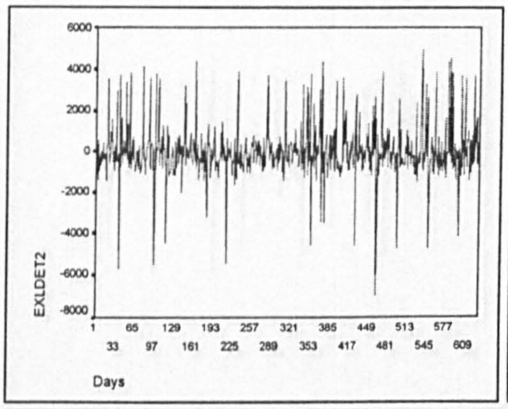
```
for i = 1:ween, % FOR loop to set up arrays of "1 to ween"
(for later graphs)
x1wee(i) = x1(i); % Setting up new variables (of size "1
to ween")
x2wee(i) = x2(i);
end                         % END of FOR loop

for i = ween+1:n-1,         % FOR loop to set up arrays of
"ween to n-1" (for later graphs)
   x1big(i) = x1(i);        % Setting up new variables (of
size "ween to n-1")
   x2big(i) = x2(i);
end                         % END of FOR loop

plot(rs,x1,'w')          % Plot of x1 against t (i.e. time
series plot of logistics eqn evolution
set(gca,'fontname','Arial','fontsize',16)  % Set font size
and name
title 'Graph of Logistics Equation'
xlabel 't'
ylabel 'x[t+1]'

figure                      % New window for next graph

plot(rs,x1,'r',rs,x2,'b:')  % Plotting two traces on one
graph (x,y,colour/style) (see <help plot>)
set(gca,'fontname','Arial','fontsize',16)  % Set font size
and name
title 'Graph of Logistics Equation, showing sensitivity to
initial conditions'
xlabel 't'
ylabel 'x[t+1]'

figure                      % New window for next graph

plot(x1wee, x2wee,'w*')       % Plot of x1 against x2 for
values "1 to ween"
set(gca,'fontname','Arial','fontsize',16)  % Set font size
and name
title 'Cycles numbered 1 to 25'
xlabel 'x[1] = 0.3'
ylabel 'x[1] = 0.3000001'

figure                      % New window for next graph

plot(x1big, x2big,'w*')       % Plot of x1 against x2 for
values "ween to n-1"
set(gca,'fontname','Arial','fontsize',16)  % Set font size
and name
```

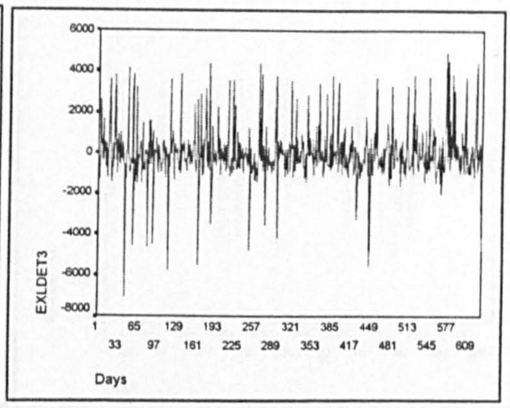
```
title 'Cycles numbered 26 to 50'
xlabel 'x[1] = 0.3'
ylabel 'x[1] = 0.3000001'
```

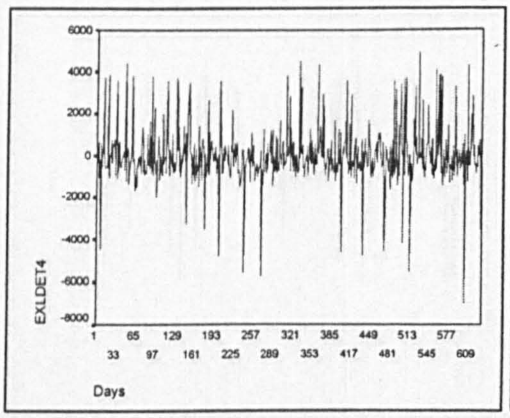
Appendix 3:
Scrambled Surrogate Data Graphs

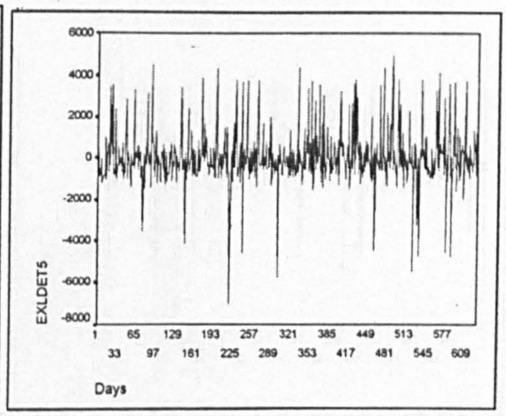


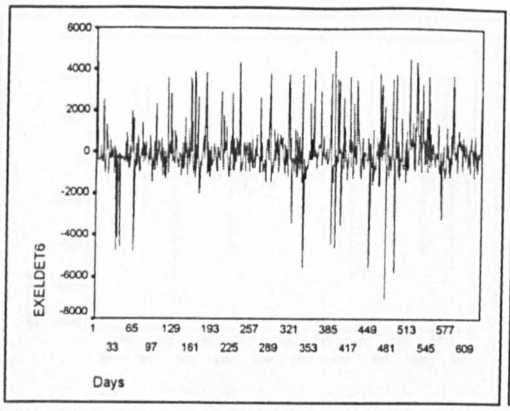


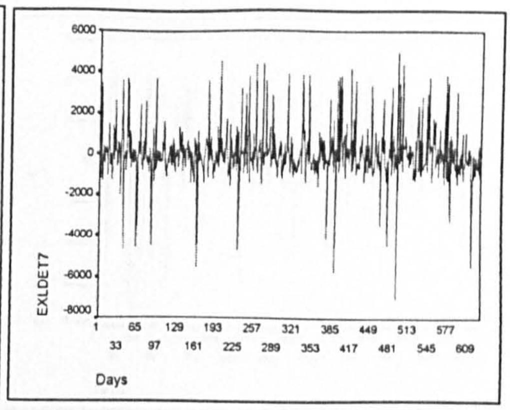


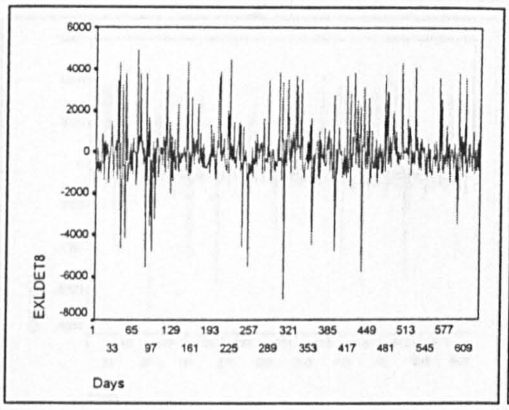


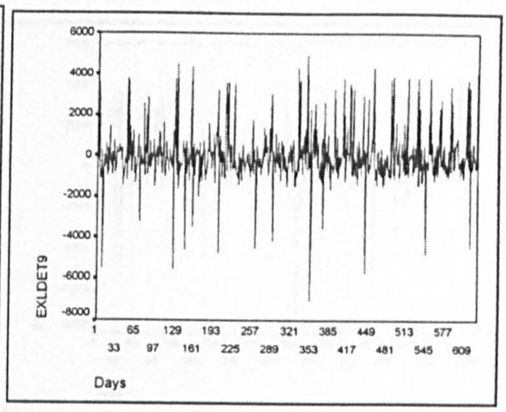


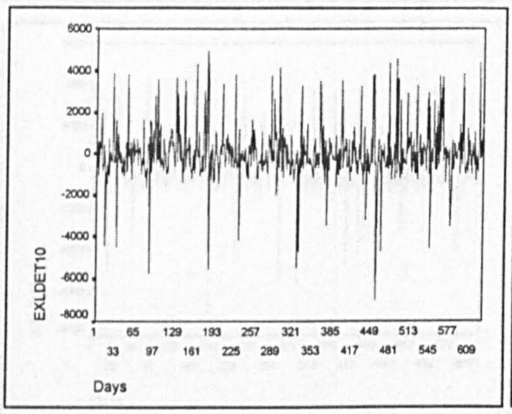



EXLDET6
6000
4000
2000
0
-2000
-4000
-6000
-8000
1 65 129 193 257 321 385 449 513 577
33 97 161 225 289 353 417 481 545 609
Days


EXLDET7
6000
4000
2000
0
-2000
-4000
-6000
-8000
1 65 129 193 257 321 385 449 513 577
33 97 161 225 289 353 417 481 545 609
Days


EXLDET8
6000
4000
2000
0
-2000
-4000
-6000
-8000
1 65 129 193 257 321 385 449 513 577
33 97 161 225 289 353 417 481 545 609
Days


EXLDET9
6000
4000
2000
0
-2000
-4000
-6000
-8000
1 65 129 193 257 321 385 449 513 577
33 97 161 225 289 353 417 481 545 609
Days


EXLDET10
6000
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-8000
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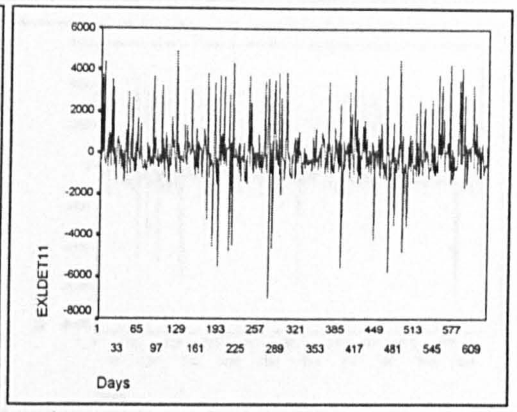
33 97 161 225 289 353 417 481 545 609
Days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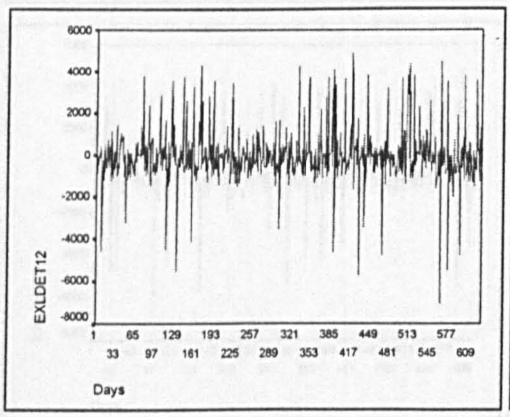
1 65 129 193 257 321 385 449 513 577
33 97 161 225 289 353 417 481 545 609
Days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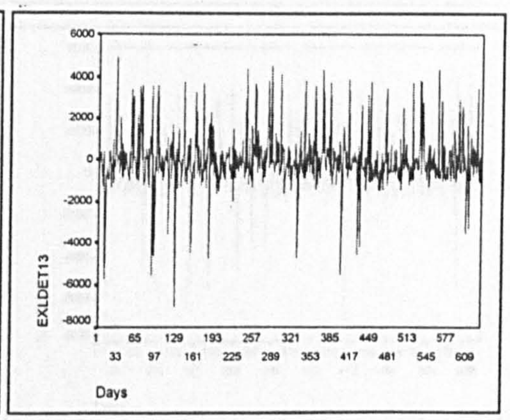
33 97 161 225 289 353 417 481 545 609
Days


EXLDET13
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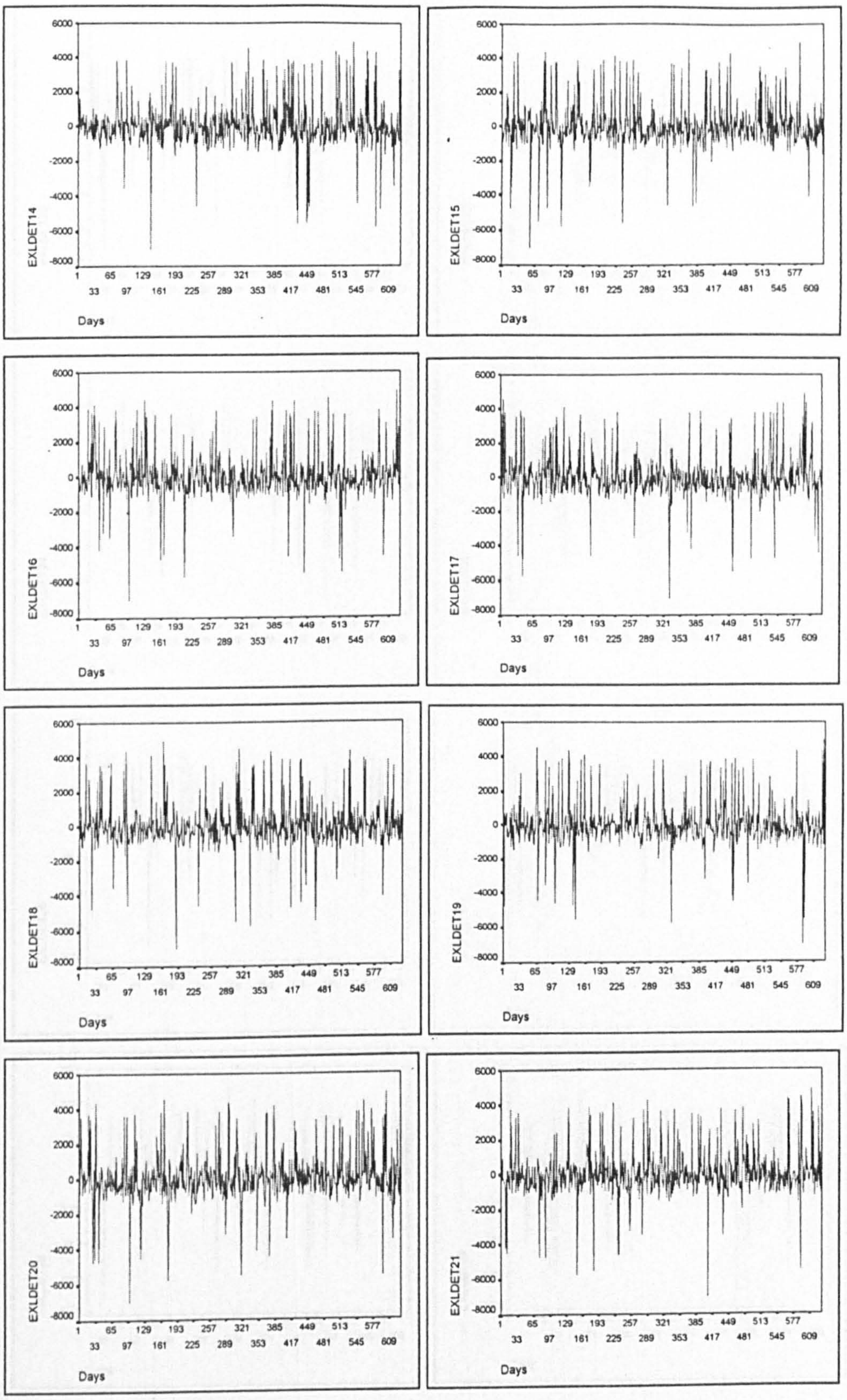
33 97 161 225 289 353 417 481 545 609
Days


EXLDET14
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EXLDET16
EXLDET17
EXLDET18
EXLDET19
EXLDET20
EXLDET21
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2000
0
-2000
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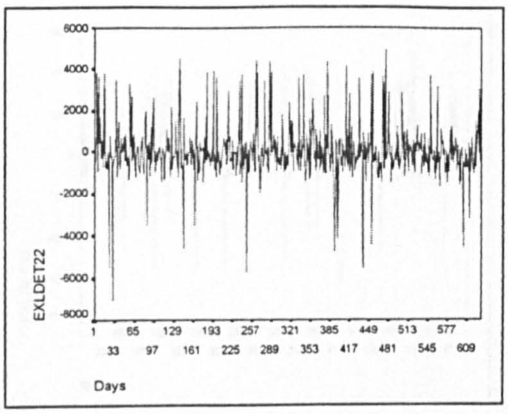
-6000
-8000
1 65 129 193 257 321 385 449 513 577
33 97 161 225 289 353 417 481 545 609
Days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EXLDET22
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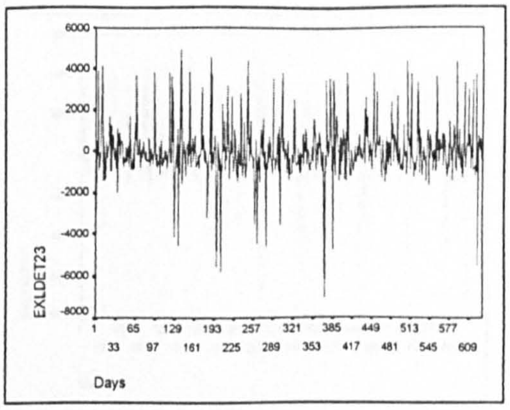
33 97 161 225 289 353 417 481 545 609
Days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EXLDET23
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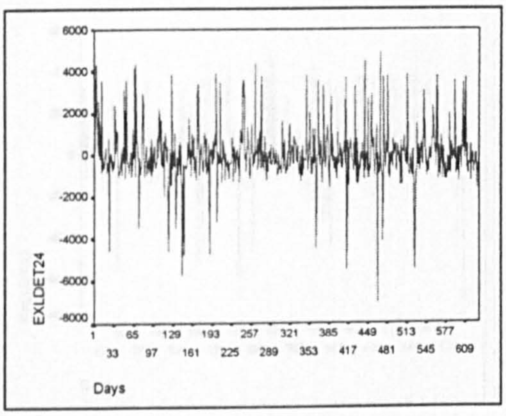
33 97 161 225 289 353 417 481 545 609
Days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-8000
EXLDET24
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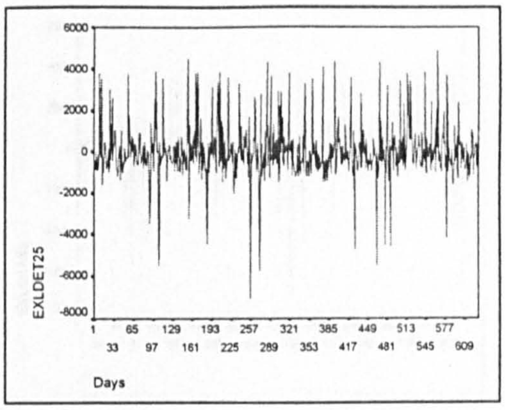
Days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EXLDET25
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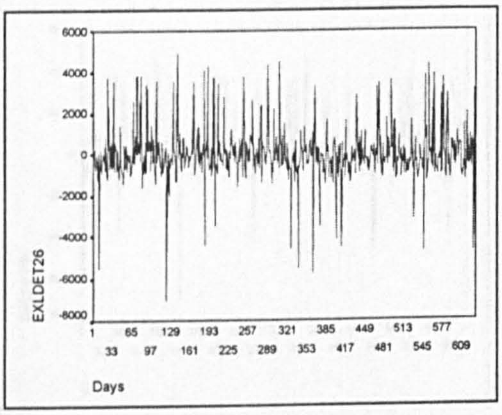
Days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EXLDET26
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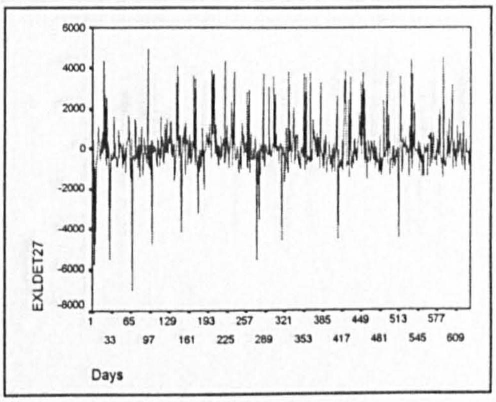
33 97 161 225 289 353 417 481 545 609
Days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EXLDET27
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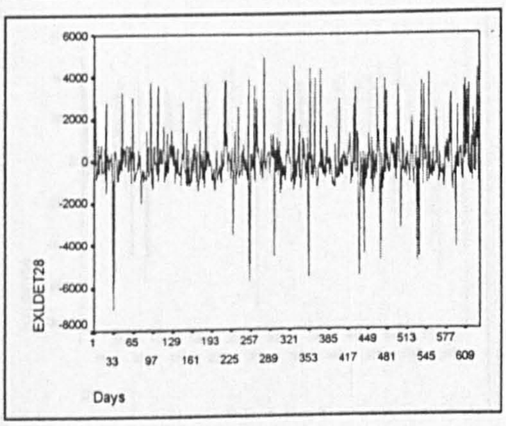
33 97 161 225 289 353 417 481 545 609
Days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EXLDET28
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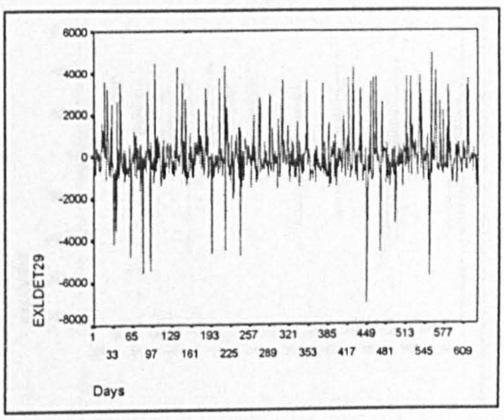
33 97 161 225 289 353 417 481 545 609
Days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-2000
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-6000
-8000
EXLDET29
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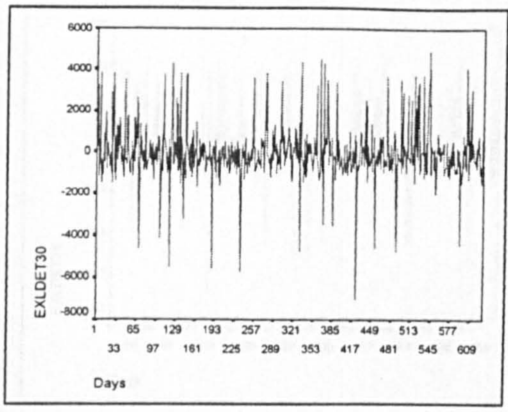
33 97 161 225 289 353 417 481 545 609
Days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-6000
-8000
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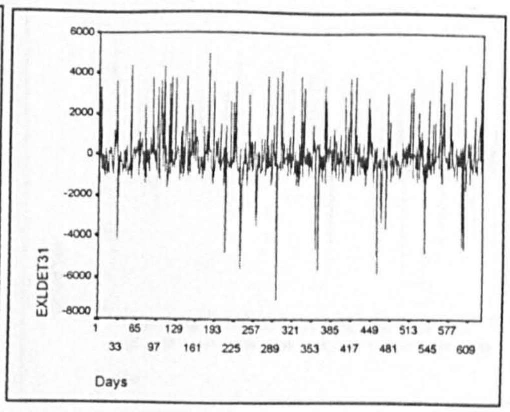
33 97 161 225 289 353 417 481 545 609
Days


EXLDET31
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2000
0
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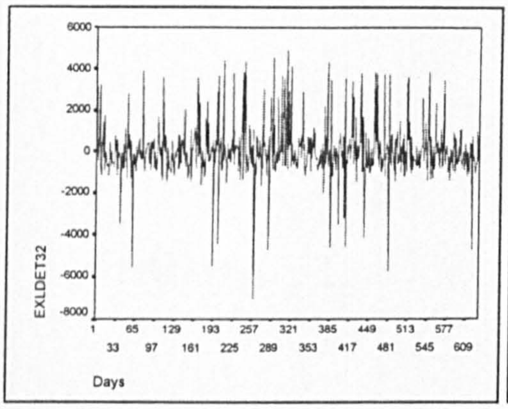
-6000
-8000
1 65 129 193 257 321 385 449 513 577
33 97 161 225 289 353 417 481 545 609
Days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-8000
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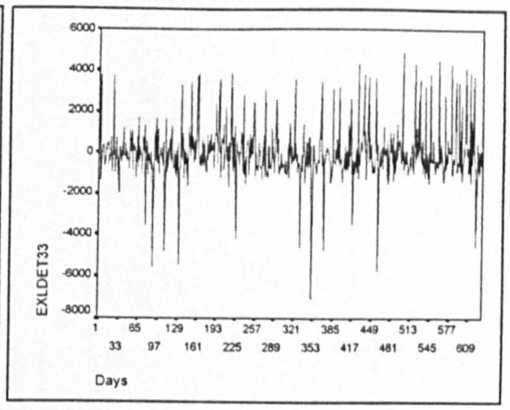
33 97 161 225 289 353 417 481 545 609
Days


EXLDET33
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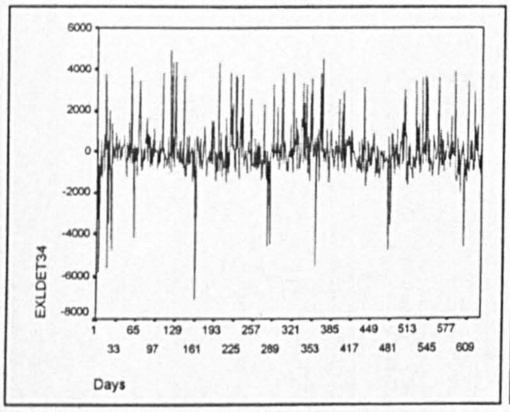
2000
0
-2000
-4000
-6000
-8000
1 65 129 193 257 321 385 449 513 577
33 97 161 225 289 353 417 481 545 609
Days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-8000
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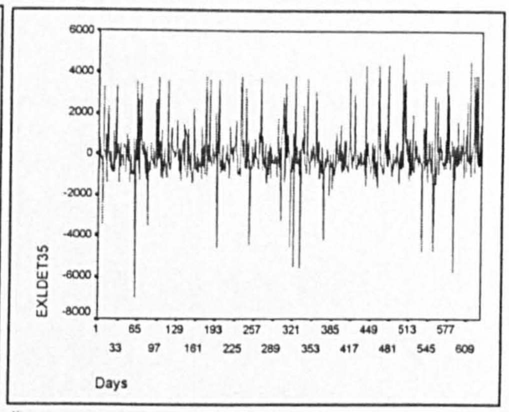
33 97 161 225 289 353 417 481 545 609
Days


EXLDET35
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2000
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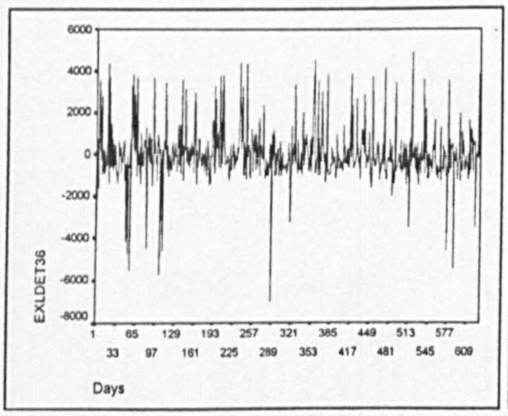
1 65 129 193 257 321 385 449 513 577
33 97 161 225 289 353 417 481 545 609
Days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2000
0
-2000
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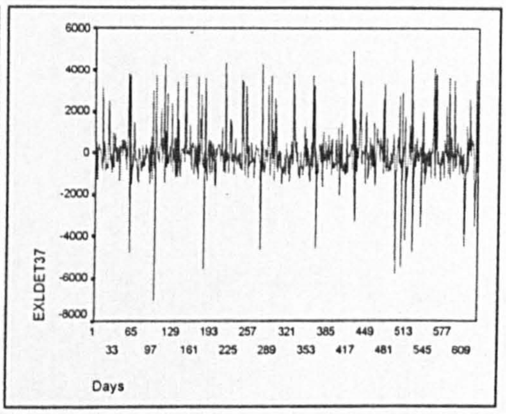
-8000
1 65 129 193 257 321 385 449 513 577
33 97 161 225 289 353 417 481 545 609
Days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2000
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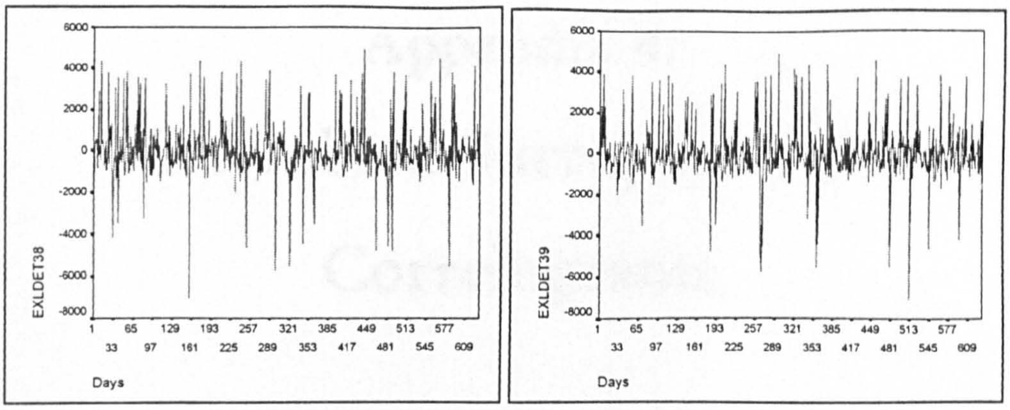
1 65 129 193 257 321 385 449 513 577
33 97 161 225 289 353 417 481 545 609
Days



6000
4000
2000
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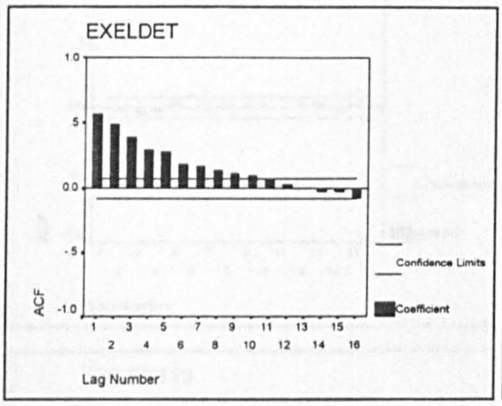
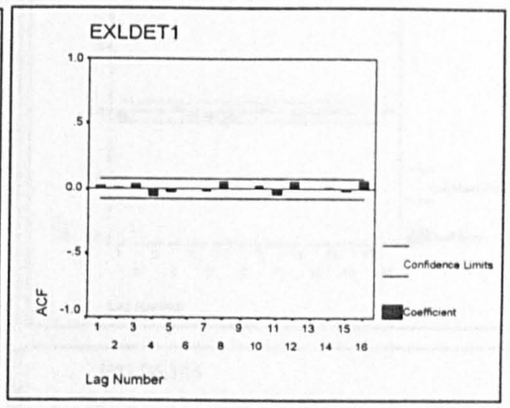
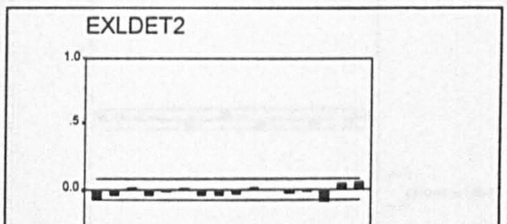
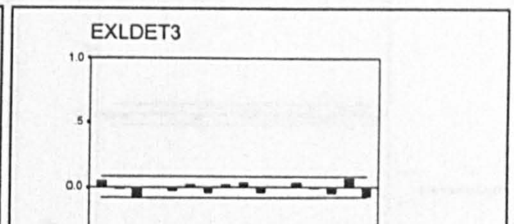
-2000
-4000
-6000
-8000
EXLDET38
1 65 129 193 257 321 385 449 513 577
33 97 161 225 289 353 417 481 545 609
Days
6000
4000
2000
0
-2000
-4000
-6000
-8000
EXLDET39
1 65 129 193 257 321 385 449 513 577
33 97 161 225 289 353 417 481 545 609
Days

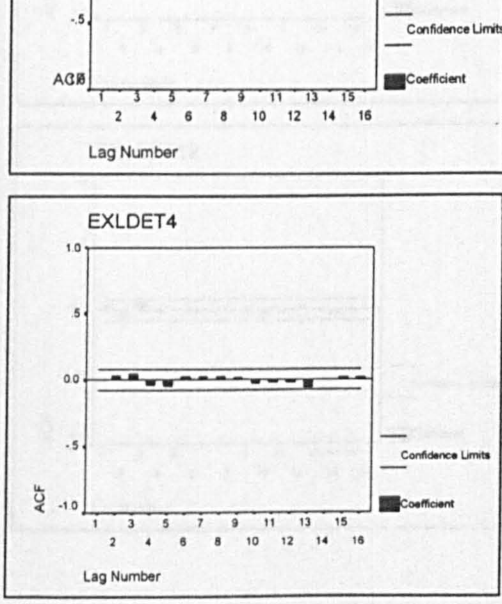
Appendix 4: Scrambled Surrogate Data Correlograms

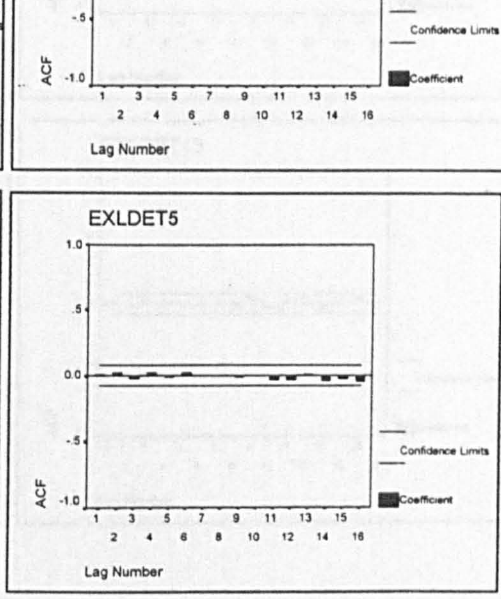


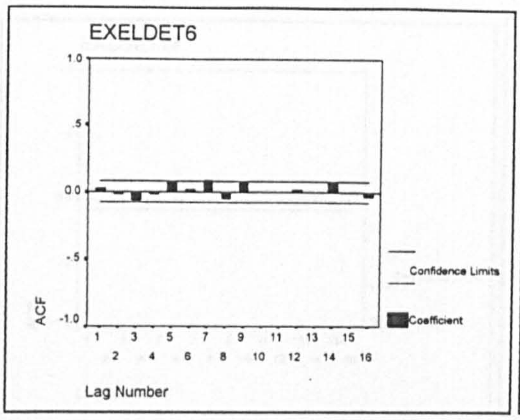











EXELDET6
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.5
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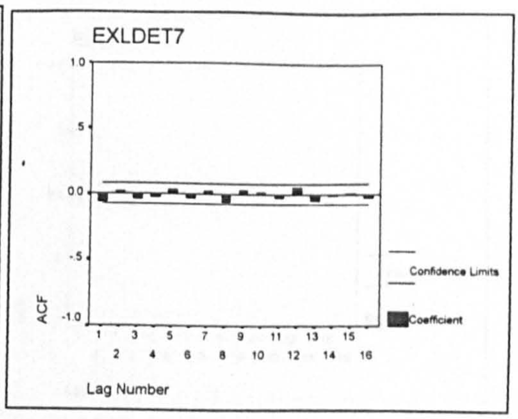
-.5
-1.0
ACF
1 3 5 7 9 11 13 15
2 4 6 8 10 12 14 16
Lag Number
Confidence Limits
Coefficient


EXLDET7
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-.5
-1.0
ACF
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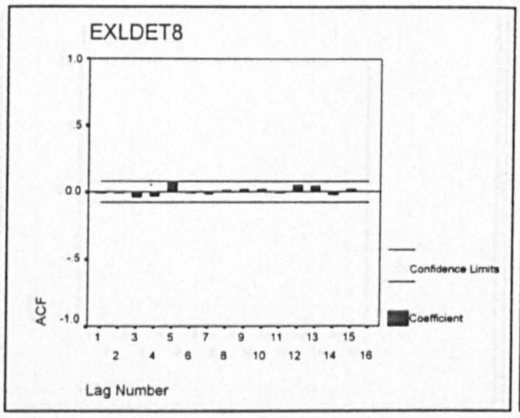
2 4 6 8 10 12 14 16
Lag Number
Confidence Limits
Coefficient


EXLDET8
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0.0
-.5
-1.0
ACF
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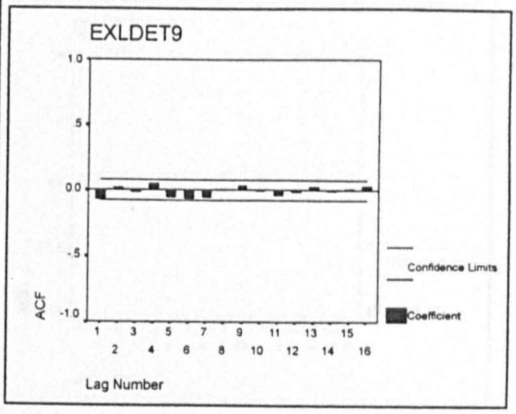
2 4 6 8 10 12 14 16
Lag Number
Confidence Limits
Coefficient


EXLDET9
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-.5
-1.0
ACF
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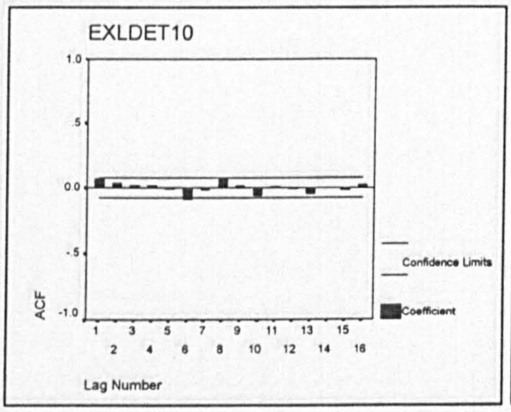
2 4 6 8 10 12 14 16
Lag Number
Confidence Limits
Coefficient


EXLDET10
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0.0
-.5
-1.0
ACF
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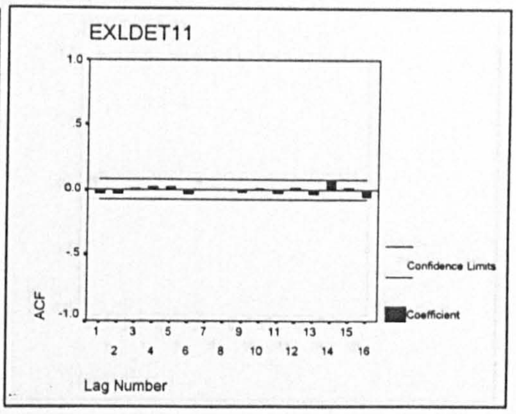
2 4 6 8 10 12 14 16
Lag Number
Confidence Limits
Coefficient


EXLDET11
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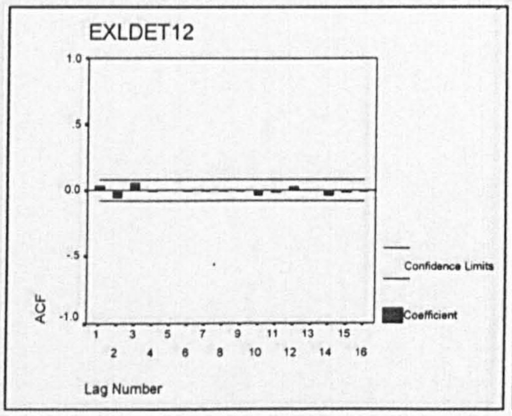
0.0
-.5
-1.0
ACF
1 3 5 7 9 11 13 15
2 4 6 8 10 12 14 16
Lag Number
Confidence Limits
Coefficient


EXLDET12
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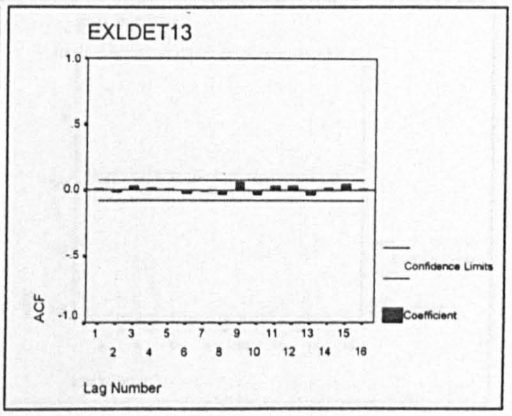
.5
0.0
-.5
-1.0
ACF
1 3 5 7 9 11 13 15
2 4 6 8 10 12 14 16
Lag Number
Confidence Limits
Coefficient


EXLDET13
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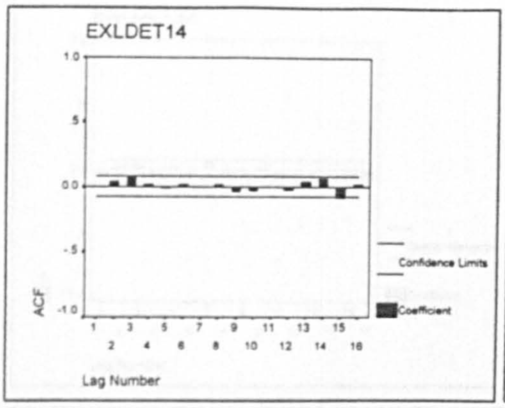
-.5
-1.0
ACF
1 3 5 7 9 11 13 15
2 4 6 8 10 12 14 16
Lag Number
Confidence Limits
Coefficient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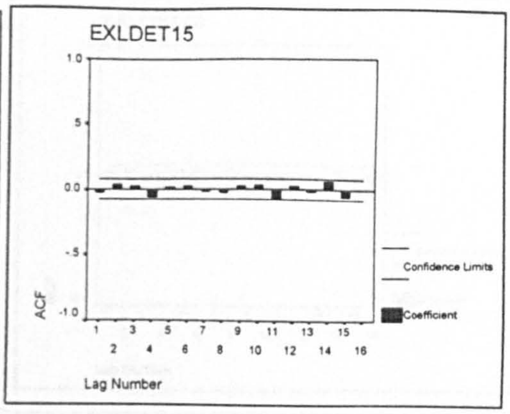
ACF
Lag Number
Confidence Limits
Coefficient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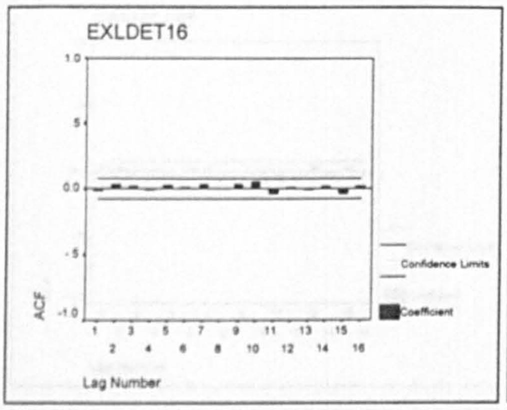
ACF
Lag Number
Confidence Limits
Coefficient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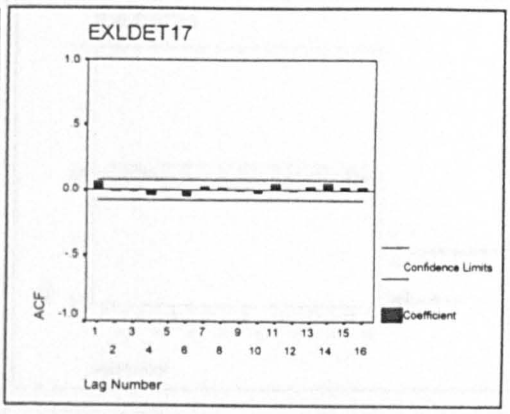
ACF
Lag Number
Confidence Limits
Coefficient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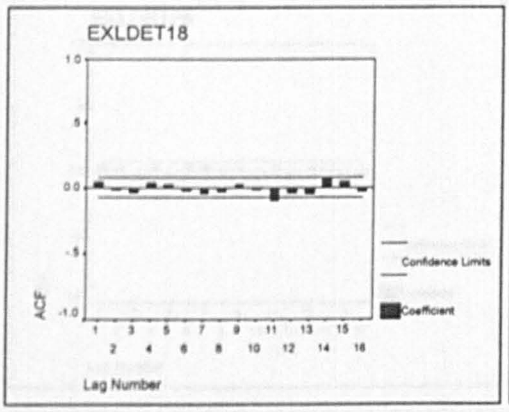
Lag Number
Confidence Limits
Coefficient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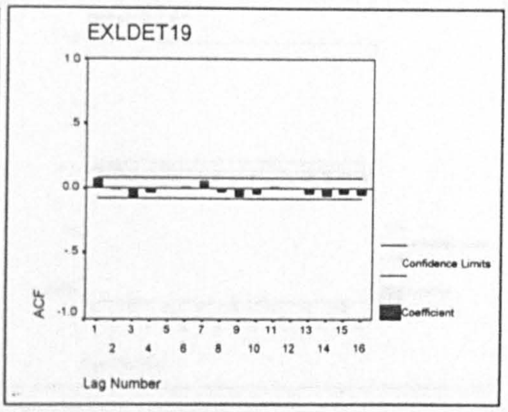
ACF
Lag Number
Confidence Limits
Coefficient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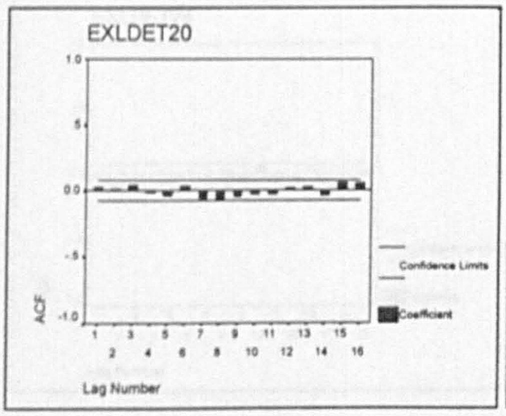
ACF
Lag Number
Confidence Limits
Coefficient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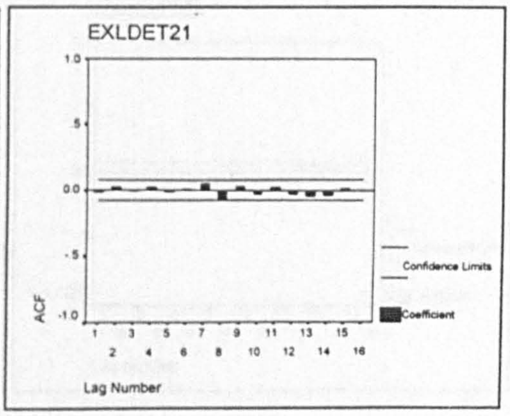
ACF
Lag Number
Confidence Limits
Coefficient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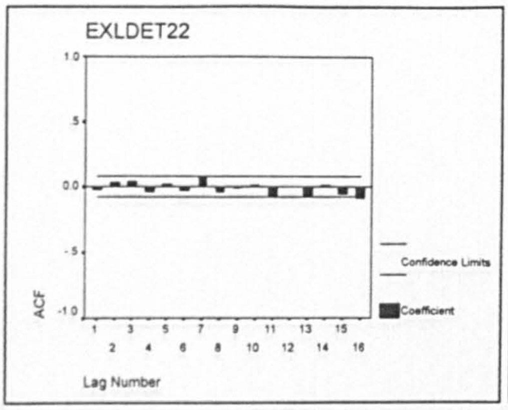
ACF
Lag Number
Confidence Limits
Coefficient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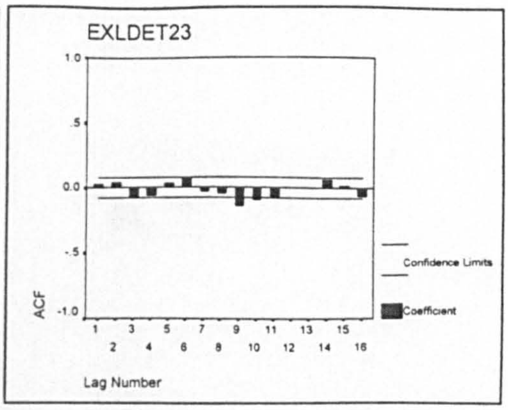
ACF
Lag Number
Confidence Limits
Coefficient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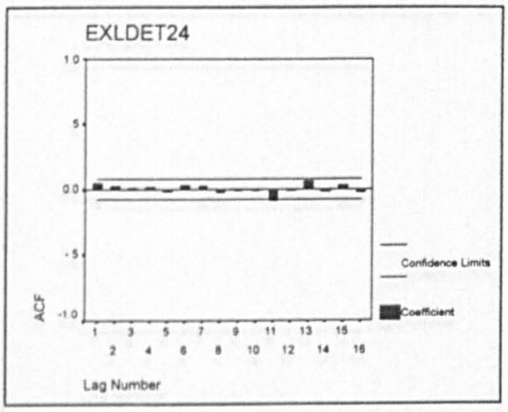
ACF
Lag Number
Confidence Limits
Coefficient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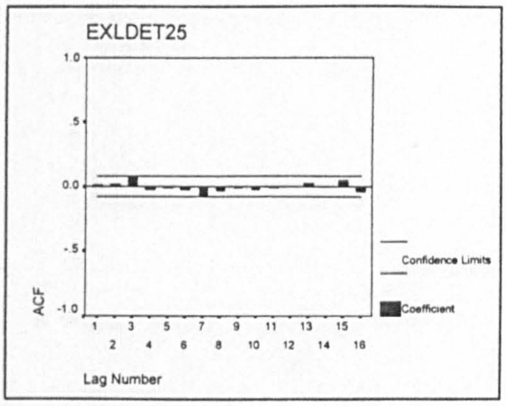
ACF
Lag Number
Confidence Limits
Coefficient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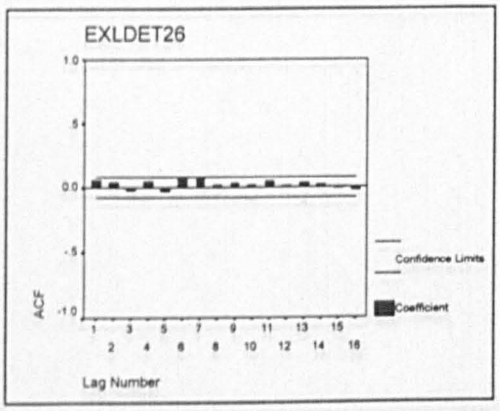
ACF
Lag Number
Confidence Limits
Coefficient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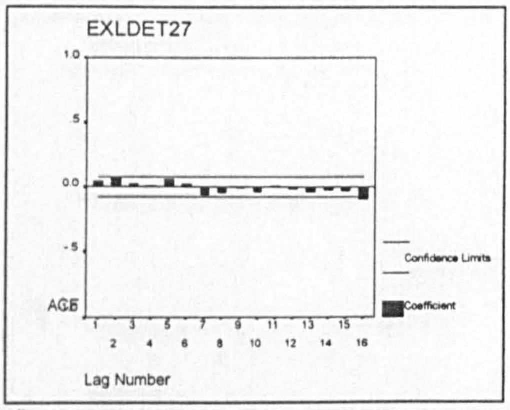
Lag Number
Confidence Limits
Coefficient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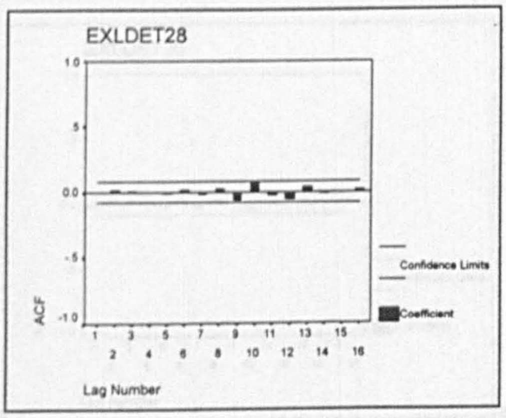
Lag Number
Confidence Limits
Coefficient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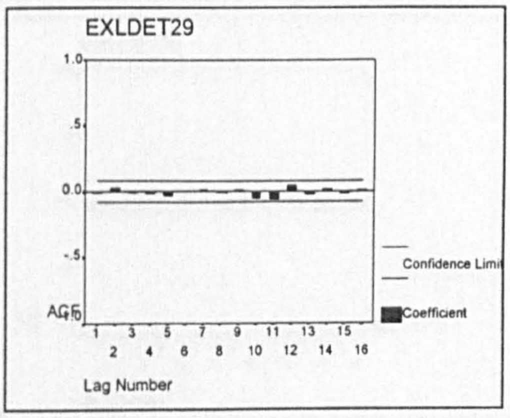
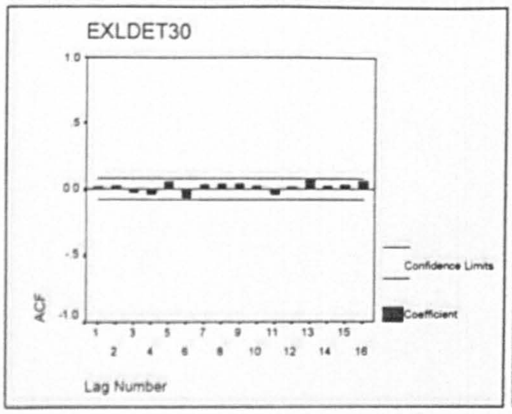
ACF
Lag Number
Confidence Limits
Coefficient


EXLDET29
Lag Number
Coefficient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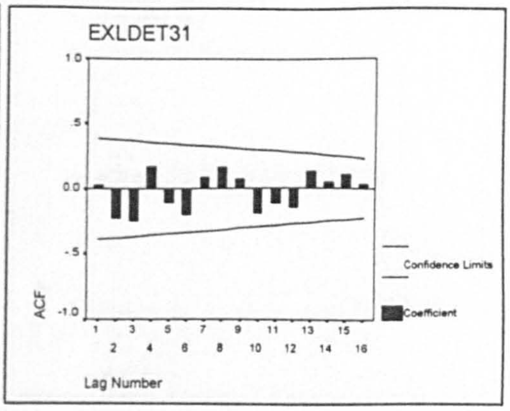
Lag Number
Confidence Limits
Coefficient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Lag Number
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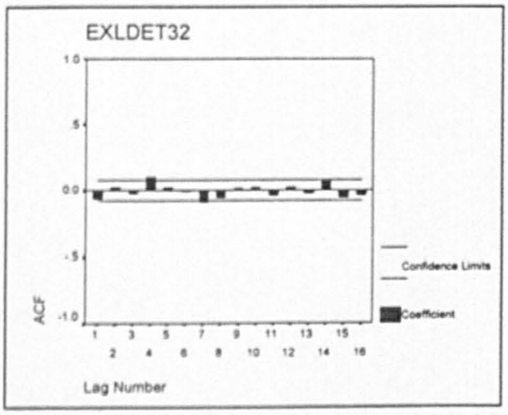
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Lag Number
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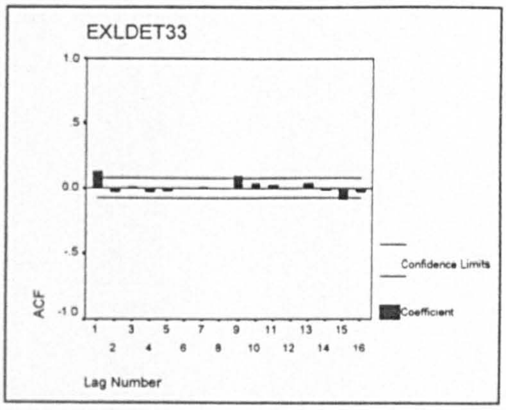
Coefficient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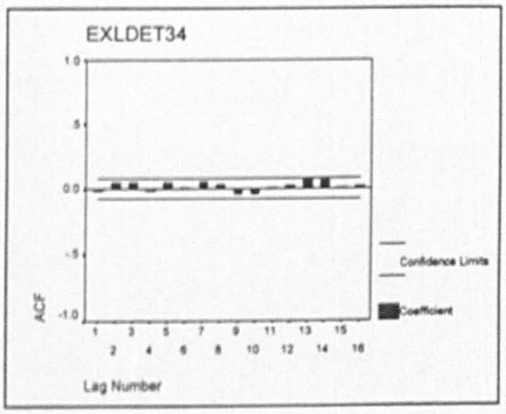
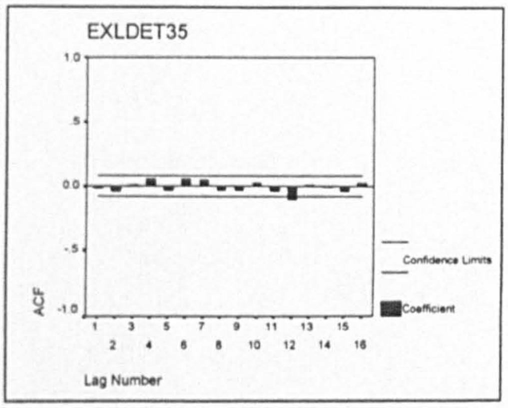
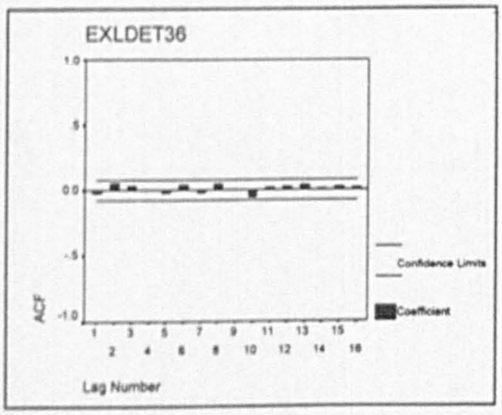
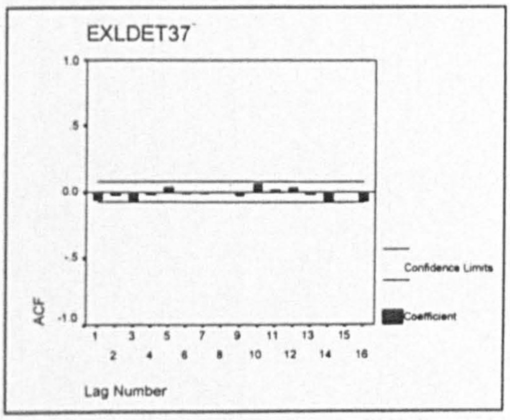
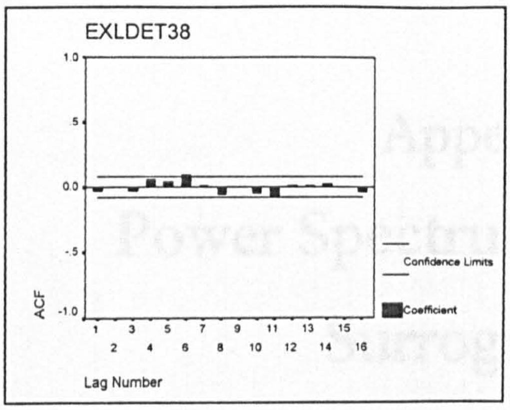
ACF
Lag Number
Confidence Limits
Coefficient

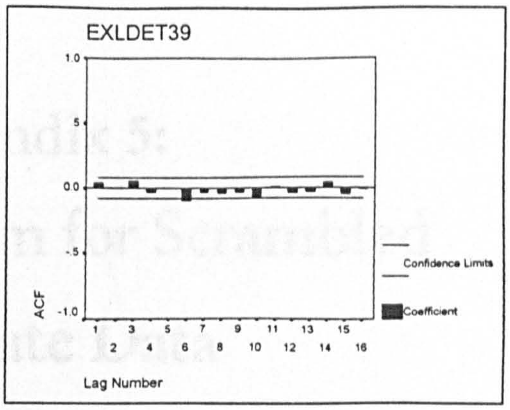

EXLDET34
ACF
Lag Number
Confidence Limits
Coefficient


EXLDET35
ACF
Lag Number
Confidence Limits
Coefficient

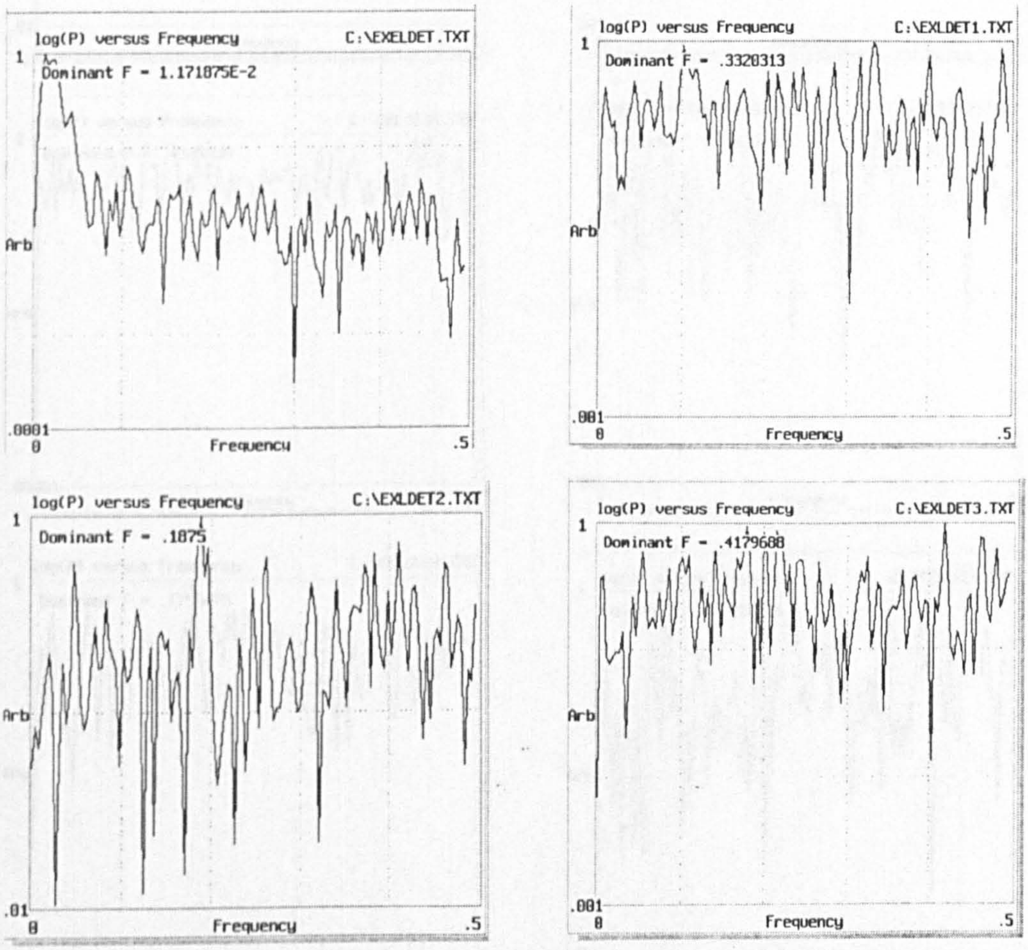

EXLDET36
ACF
Lag Number
Confidence Limits
Coefficient

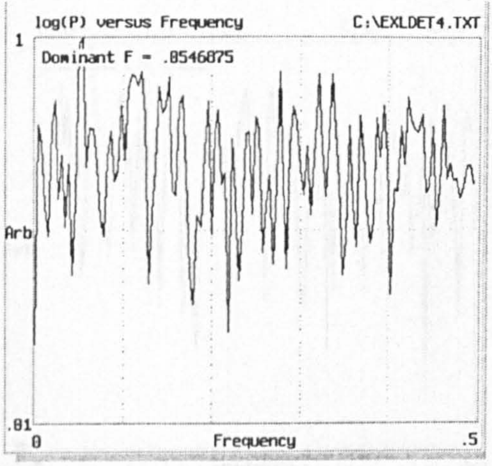

EXLDET37
ACF
Lag Number
Confidence Limits
Coefficient

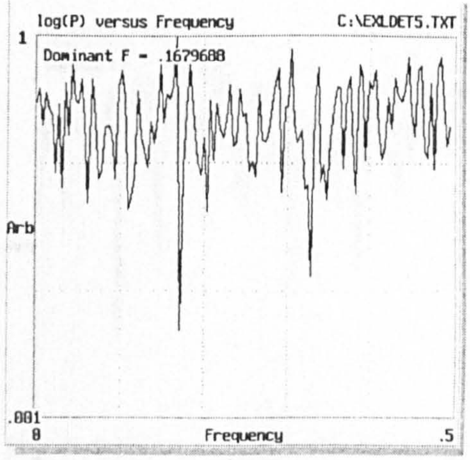

EXLDET38
ACF
1.0
.5
0.0
-.5
-1.0
1 3 5 7 9 11 13 15
2 4 6 8 10 12 14 16
Lag Number
Confidence Limits
Coefficient

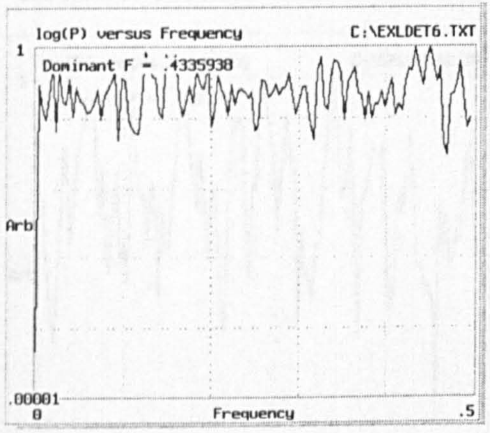

EXLDET39
ACF
1.0
.5
0.0
-.5
-1.0
1 3 5 7 9 11 13 15
2 4 6 8 10 12 14 16
Lag Number
Confidence Limits
Coefficient

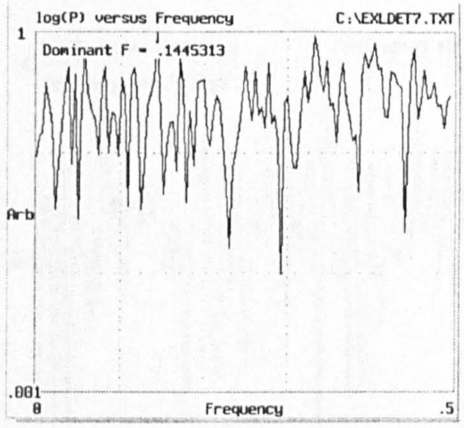
Appendix 5: Power Spectrum for Scrambled Surrogate Data

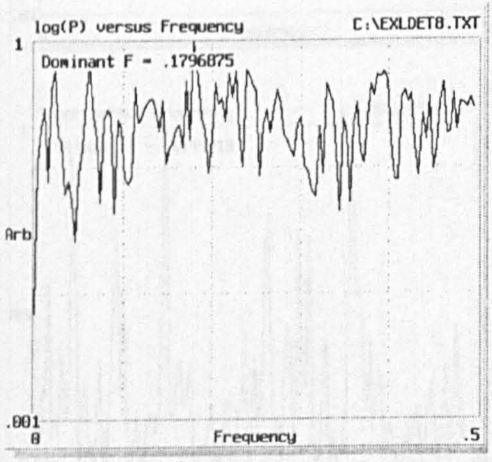


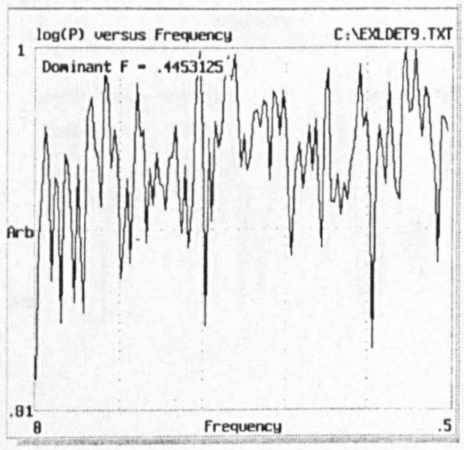

log(P) versus Frequency
C:\EXLDET4.TXT
Dominant F = .0546875
1
Arb
.01
0
Frequency
.5

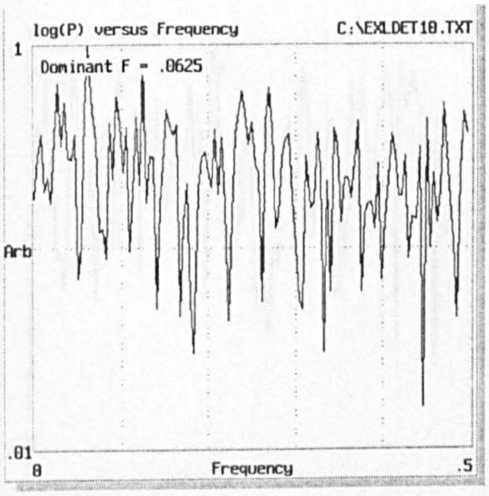

log(P) versus Frequency
C:\EXLDET5.TXT
Dominant F = .1679688
1
Arb
.001
0
Frequency
.5

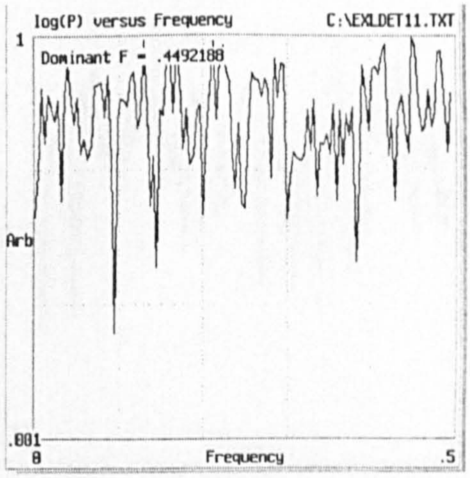

log(P) versus Frequency
C:\EXLDET6.TXT
Dominant F = .4335938
1
Arb
.00001
0
Frequency
.5

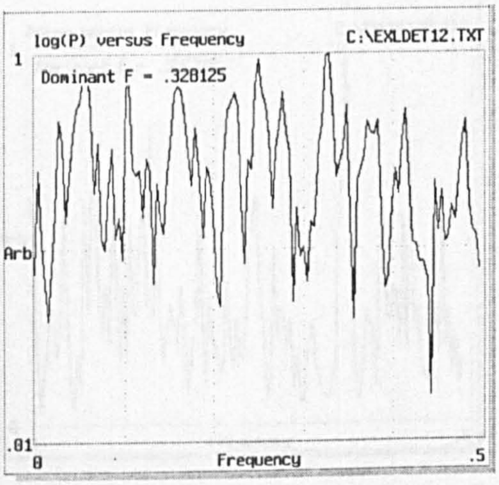

log(P) versus Frequency
C:\EXLDET7.TXT
Dominant F = .1445313
1
Arb
.001
0
Frequency
.5

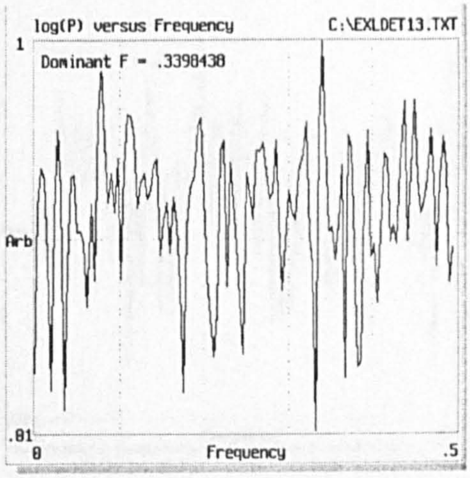

log(P) versus Frequency
C:\EXLDET8.TXT
Dominant F = .1796875
1
Arb
.001
0
Frequency
.5

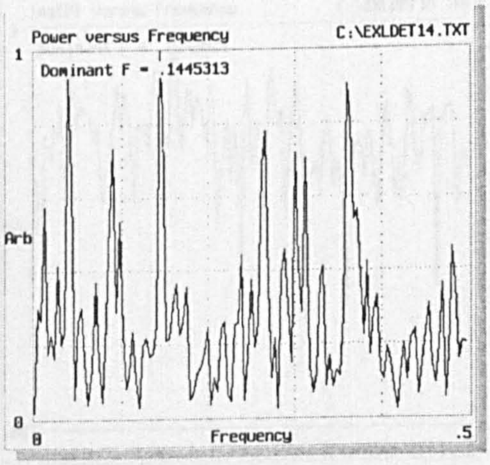

log(P) versus Frequency
C:\EXLDET9.TXT
Dominant F = .4453125
1
Arb
.01
0
Frequency
.5

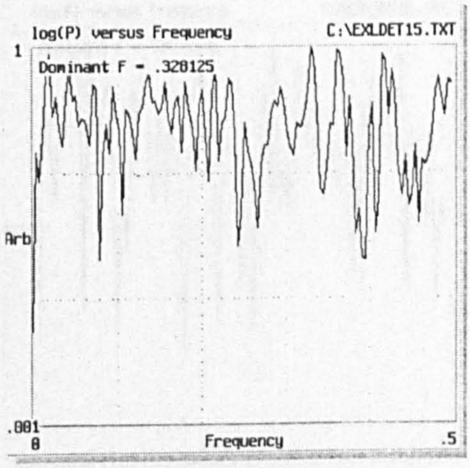

log(P) versus Frequency
C:\EXLDET10.TXT
Dominant F = .0625
1
Arb
.01
0
Frequency
.5

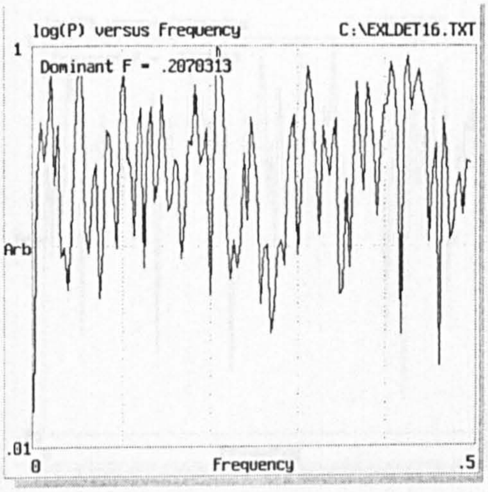

log(P) versus Frequency
C:\EXLDET11.TXT
Dominant F = .4492188
1
Arb
.001
0
Frequency
.5

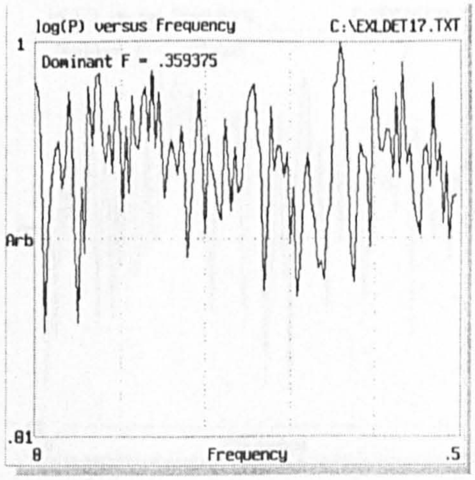

log(P) versus Frequency
C:\EXLDET12.TXT
Dominant F = .328125
1
Arb
.01
0
Frequency
.5

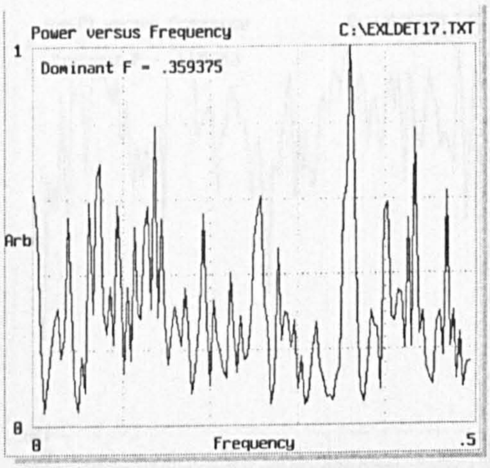

log(P) versus Frequency
C:\EXLDET13.TXT
Dominant F = .3398438
1
Arb
.01
0
Frequency
.5

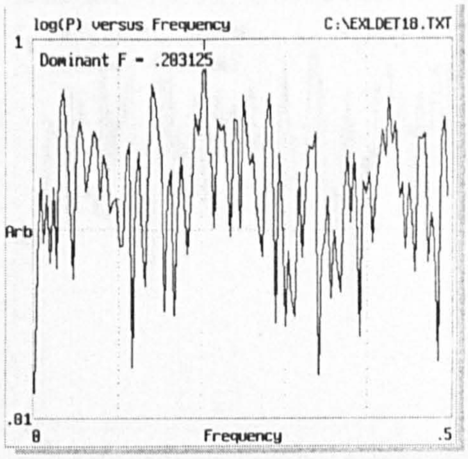

Power versus Frequency
C:\EXLDET14.TXT
Dominant F = .1445313
1
Arb
0
0
Frequency
.5

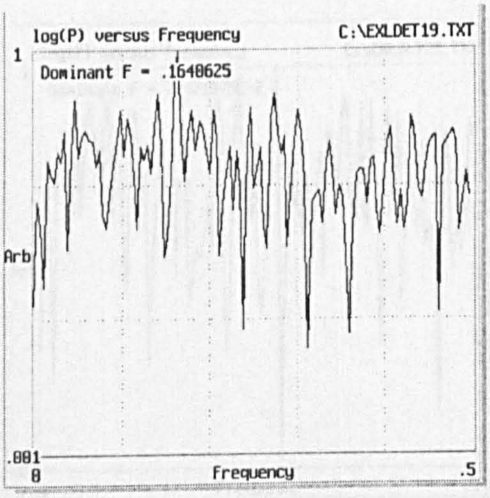

log(P) versus Frequency
C:\EXLDET15.TXT
Dominant F = .328125
1
Arb
.001
0
Frequency
.5

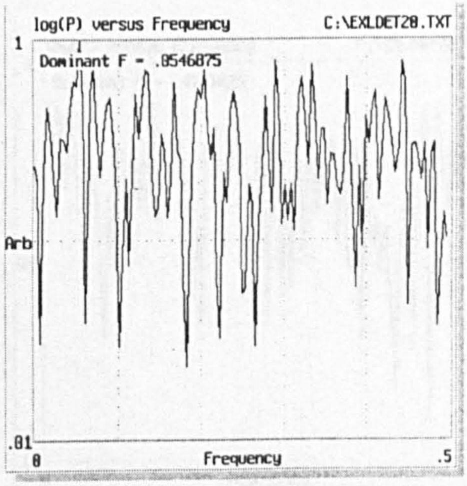

log(P) versus Frequency
C:\EXLDET16.TXT
Dominant F = .2070313
1
Arb
.01
0
Frequency
.5

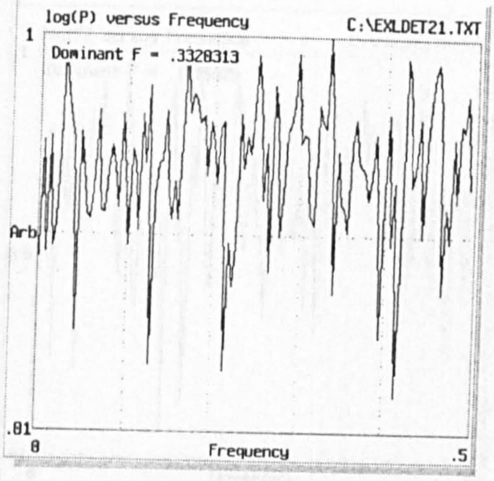

log(P) versus Frequency
C:\EXLDET17.TXT
Dominant F = .359375
1
Arb
.01
0
Frequency
.5

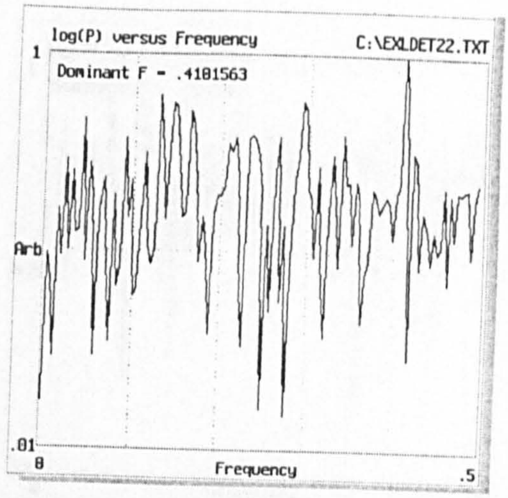

Power versus Frequency
C:\EXLDET17.TXT
Dominant F = .359375
1
Arb
0
0
Frequency
.5

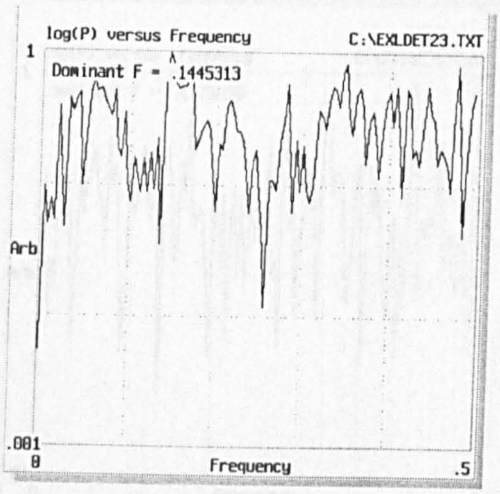

log(P) versus Frequency
C:\EXLDET18.TXT
Dominant F = .203125
1
Arb
.01
0
Frequency
.5

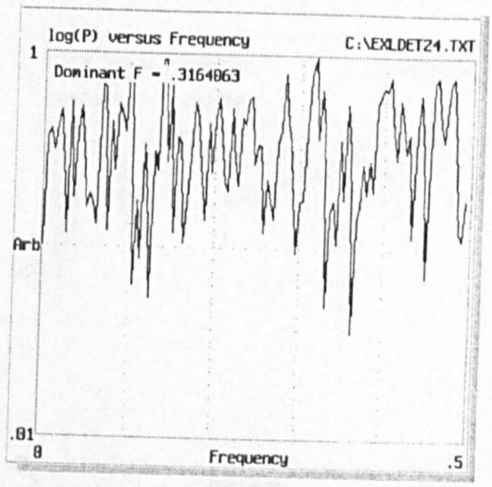

log(P) versus Frequency
C:\EXLDET19.TXT
Dominant F = .1640625
1
Arb
.001
0
Frequency
.5

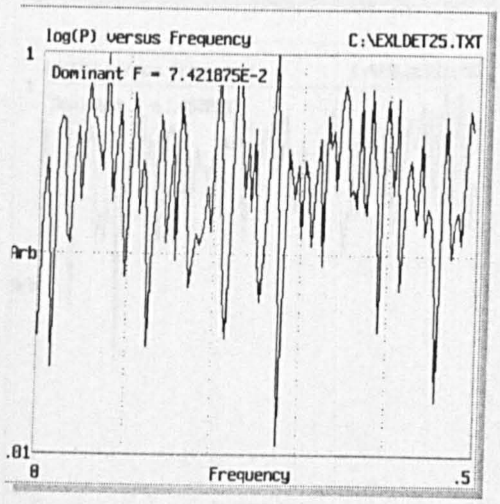

log(P) versus Frequency
C:\EXLDET20.TXT
Dominant F = .0546875
1
Arb
.01
0
Frequency
.5

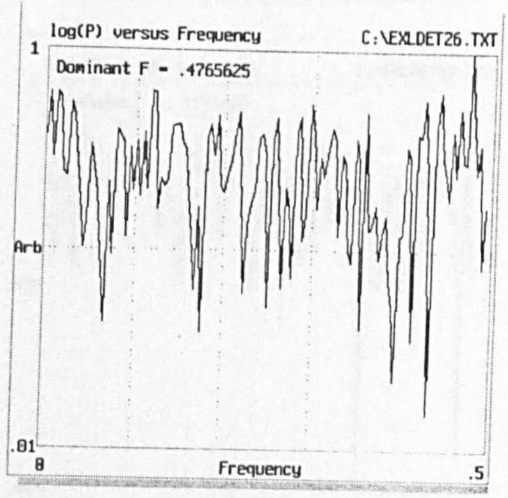

log(P) versus Frequency
C:\EXLDET21.TXT
Dominant F = .3328313
1
Arb
.01
0
Frequency
.5

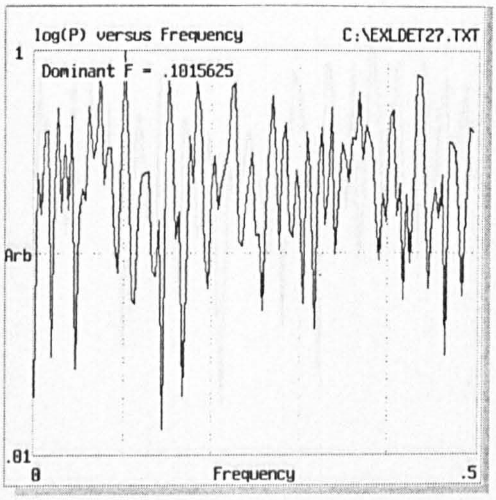

log(P) versus Frequency
C:\EXLDET22.TXT
Dominant F = .4101563
1
Arb
.01
0
Frequency
.5

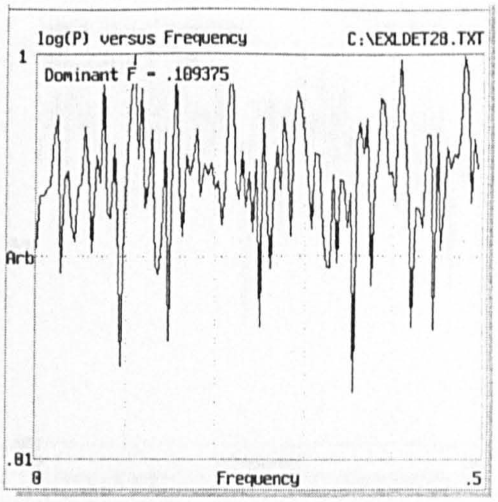

log(P) versus Frequency
C:\EXLDET23.TXT
Dominant F = .1445313
1
Arb
.001
0
Frequency
.5

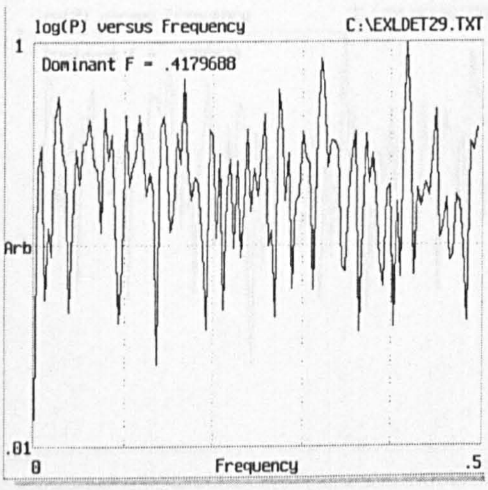

log(P) versus Frequency
C:\EXLDET24.TXT
Dominant F = .3164063
1
Arb
.01
0
Frequency
.5

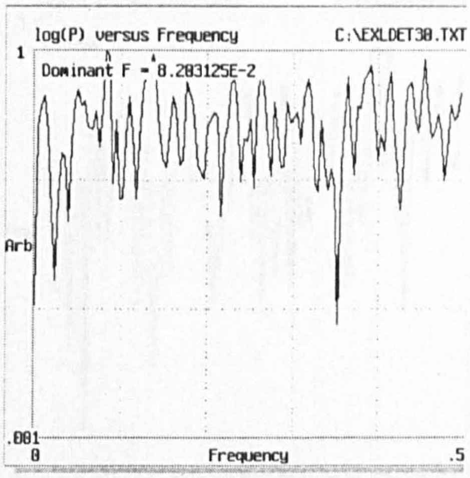

log(P) versus Frequency
C:\EXLDET25.TXT
Dominant F = 7.421875E-2
1
Arb
.01
0
Frequency
.5

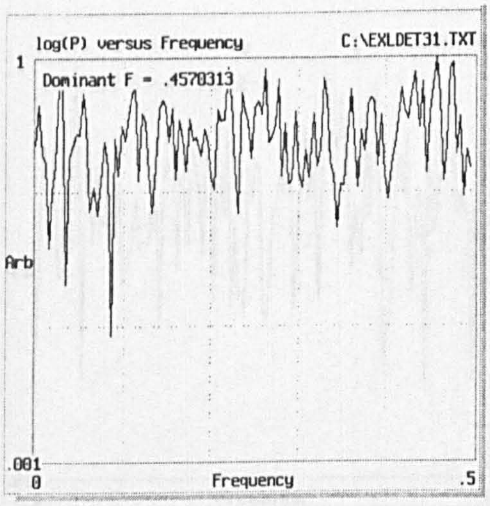

log(P) versus Frequency
C:\EXLDET26.TXT
Dominant F = .4765625
1
Arb
.01
0
Frequency
.5

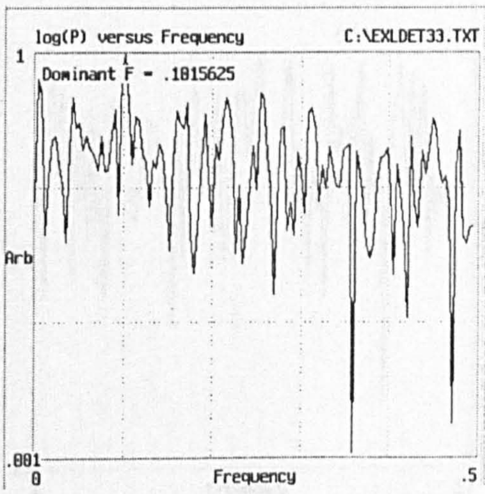

log(P) versus Frequency
C:\EXLDET27.TXT
Dominant F = .1015625
1
Arb
.01
0
Frequency
.5

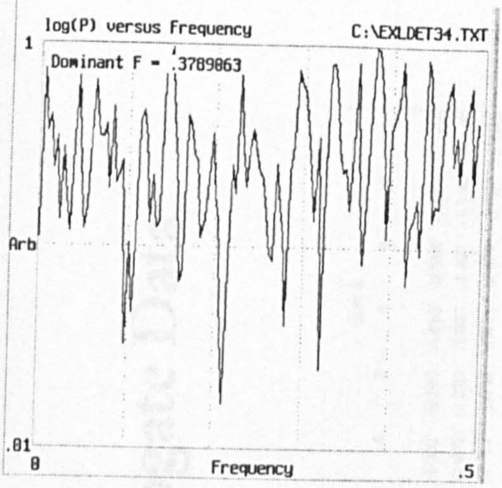

log(P) versus Frequency
C:\EXLDET28.TXT
Dominant F = .109375
1
Arb
.01
0
Frequency
.5

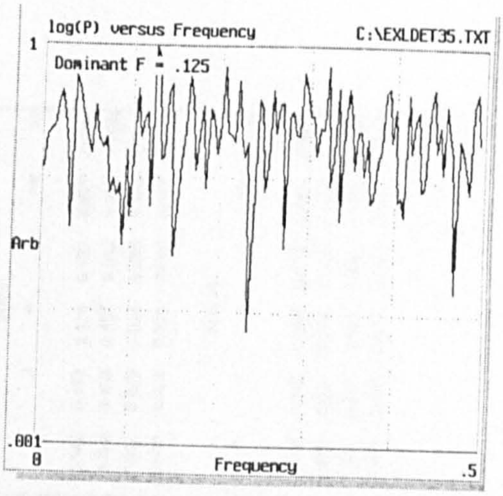

log(P) versus Frequency
C:\EXLDET29.TXT
Dominant F = .4179688
1
Arb
.01
0
Frequency
.5

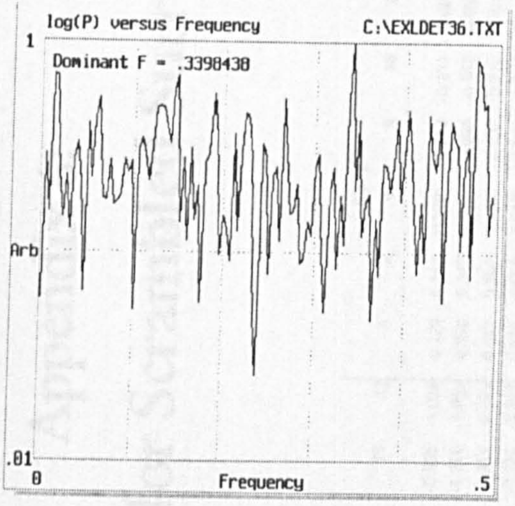

log(P) versus Frequency
C:\EXLDET30.TXT
Dominant F = 8.203125E-2
1
Arb
.001
0
Frequency
.5

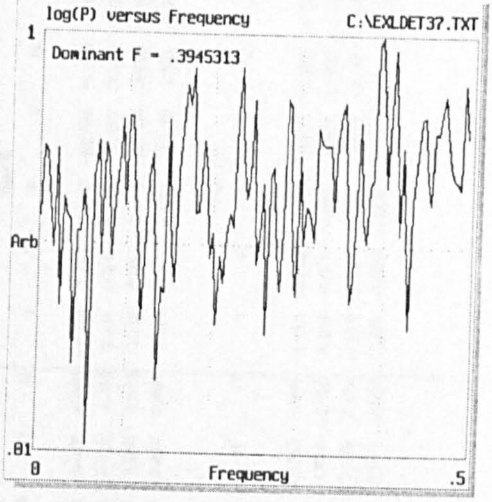

log(P) versus Frequency
C:\EXLDET31.TXT
Dominant F = .4570313
1
Arb
.001
0
Frequency
.5

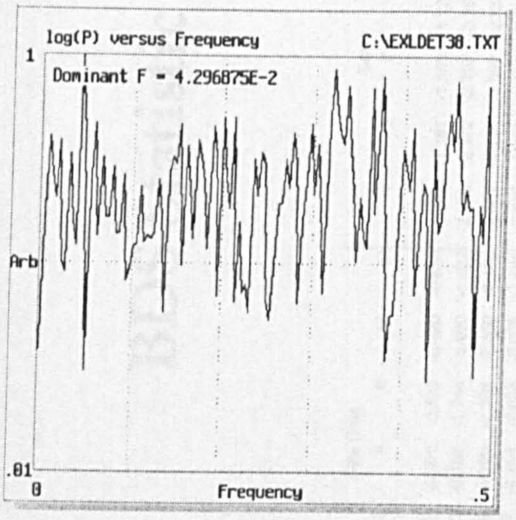

log(P) versus Frequency
C:\EXLDET33.TXT
Dominant F = .1015625
1
Arb
.001
0
Frequency
.5

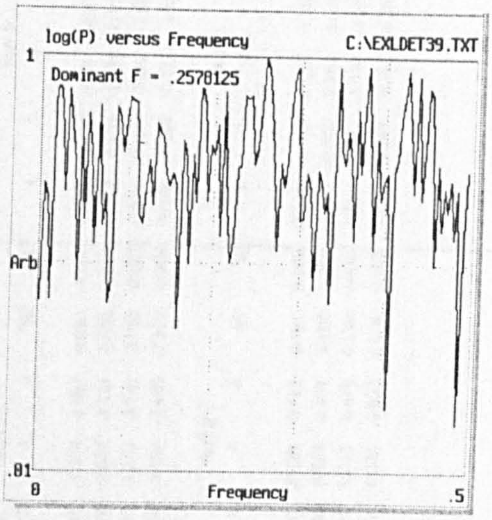

log(P) versus Frequency
C:\EXLDET34.TXT
Dominant F = .3789063
1
Arb
.01
0
Frequency
.5


log(P) versus Frequency
C:\EXLDET35.TXT
Dominant F = .125
1
Arb
.001
0
Frequency
.5


log(P) versus Frequency
C:\EXLDET36.TXT
Dominant F = .3398438
1
Arb
.01
0
Frequency
.5


log(P) versus Frequency
C:\EXLDET37.TXT
Dominant F = .3945313
1
Arb
.01
0
Frequency
.5


log(P) versus Frequency
C:\EXLDET38.TXT
Dominant F = 4.296875E-2
1
Arb
.01
0
Frequency
.5


log(P) versus Frequency
C:\EXLDET39.TXT
Dominant F = .2578125
1
Arb
.01
0
Frequency
.5

Appendix 6:

BDS Statistic for Scrambled Surrogate Data

Raw Data

n	1	2	4	8	16	32
D						
2	0.339	0.118	-0.201	-0.733	-0.420	-0.634
3	-0.192	-0.510	-0.108	-1.744	-1.400	-1.423
4	-1.000	-1.174	-0.185	-2.388	-2.360	-2.426
5	-1.580	-1.649	-2.244	-2.638	-3.086	-2.749

Surr 1

n	1	2	4	8	16	32
D						
2	-1.191	-1.181	-1.486	-1.128	-0.605	-1.023
3	-2.290	-2.532	-2.707	-2.257	-1.375	-1.950
4	-2.973	-3.151	-3.307	-2.814	-2.311	-2.371
5	-3.146	-3.202	-3.251	-2.902	-3.131	-2.319

Surr 2

n	1	2	4	8	16	32
D						
2	0.129	0.112	-0.209	-0.213	-0.211	0.069
3	0.380	0.340	0.016	0.034	0.013	0.338
4	0.527	0.501	0.189	0.207	0.210	0.490
5	0.644	0.609	0.318	0.329	0.348	0.701

Surr 3

n	1	2	4	8	16	32
D						
2	-1.332	-0.800	-0.815	-0.556	-0.568	-0.664
3	-2.603	-1.968	-1.803	-1.497	-1.259	-1.375
4	-3.175	-3.096	-2.811	-2.471	-2.151	-1.785
5	-3.231	-3.812	-3.602	-3.265	-2.742	-1.871

Surr 4

n	1	2	4	8	16	32
D						
2	-0.680	-1.285	-1.354	-1.091	-0.883	-0.898
3	-1.742	-2.623	-2.574	-2.131	-2.036	-1.839
4	-2.841	-3.317	-3.281	-2.741	-2.786	-2.353
5	-3.659	-3.332	-3.226	-2.882	-2.976	-2.359

Surr 5

n	1	2	4	8	16	32
D						
2	-1.388	-1.404	-1.341	-0.979	-1.397	-0.199
3	-2.767	-2.709	-2.419	-2.162	-2.716	-1.164
4	-3.375	-3.224	-3.061	-2.897	-3.282	-2.142
5	-3.429	-3.109	-3.152	-3.074	-3.309	-2.990

Surr 6

n	1	2	4	8	16	32
D						
2	-1.296	-1.157	-1.130	-12.226	-1.108	-1.437
3	-2.517	-2.249	-2.315	-2.189	-2.183	-2.393
4	-3.119	-2.861	-2.884	-2.684	-2.796	-3.201
5	-3.124	-2.971	-2.845	-2.648	-2.851	-3.312

Surr 7

n	1	2	4	8	16	32
D						
2	0.142	0.137	0.134	0.121	-0.021	-0.266
3	0.352	0.402	0.352	0.343	0.001	0.006
4	0.497	0.563	0.507	0.528	0.183	0.215
5	0.619	0.668	0.620	0.632	0.318	0.405

Surr 8

n	1	2	4	8	16	32
D						
2	0.132	0.153	0.126	0.121	0.191	0.263
3	0.355	0.392	0.359	0.331	0.410	0.349
4	0.527	0.545	0.516	0.478	0.536	0.445
5	0.619	0.672	0.656	0.560	0.624	0.555

Surr 9

n	1	2	4	8	16	32
D						
2	-0.704	-1.449	-1.226	-1.304	-0.703	-1.015
3	-1.805	-2.690	-2.552	-2.570	-1.668	-2.139
4	-2.588	-3.307	-3.136	-3.209	-2.689	-2.703
5	-3.212	-3.381	-3.152	-3.235	-3.384	-2.902

Surr 10

n	1	2	4	8	16	32
D						
2	-1.165	-1.356	-1.251	-1.147	-1.258	-0.593
3	-2.394	-2.577	-2.368	-2.407	-2.483	-1.395
4	-3.124	-3.026	-2.972	-2.998	-3.142	-2.088
5	-3.238	-3.026	-3.069	-3.061	-3.240	-2.691

Surr 11

n	1	2	4	8	16	32
D						
2	-1.278	-1.369	-1.280	-0.553	-0.645	-0.087
3	-2.570	-2.684	-2.378	-1.512	-1.562	-0.309
4	-3.111	-3.258	-2.846	-2.291	-2.449	-0.941
5	-3.155	-3.222	-2.873	-2.932	-3.021	-1.439

Surr 12

n	1	2	4	8	16	32
D						
2	-1.087	-0.515	-0.772	-0.504	-0.789	-0.995
3	-2.389	-1.616	-1.663	-1.629	-1.747	-2.001
4	-3.059	-2.777	-2.423	-2.623	-2.862	-2.661
5	-3.217	-3.508	-3.189	-3.265	-3.572	-2.848

Surr 13

n	1	2	4	8	16	32
D						
2	-1.238	-1.177	-1.128	-1.367	-1.176	-0.886
3	-2.429	-2.215	-2.384	-2.600	-2.145	-1.693
4	-3.112	-2.895	-2.947	-3.168	-2.643	-1.811
5	-3.175	-2.970	-3.019	-3.089	-2.617	-1.679

Surr 14

n	1	2	4	8	16	32
D						
2	-1.369	-1.067	-1.335	-0.520	-1.235	-1.377
3	-2.551	-2.282	-2.571	-1.709	-2.331	-2.794
4	-3.166	-2.917	-3.172	-2.932	-2.992	-3.499
5	-3.224	-3.045	-3.160	-3.821	-3.058	-3.886

Surr 15

n	1	2	4	8	16	32
D						
2	-0.878	-0.666	-0.878	-0.750	-1.042	-0.313
3	-1.979	-1.856	-2.012	-1.599	-1.844	-0.900
4	-3.031	-2.932	-3.066	-2.371	-2.527	-1.288
5	-3.831	-3.699	-3.704	-2.914	-2.677	-1.548

Surr 16

n	1	2	4	8	16	32
D						
2	-0.576	-0.769	-0.786	-0.488	-0.761	-0.224
3	-1.631	-1.937	-1.822	-1.372	-1.508	-0.568
4	-2.717	-3.075	-2.931	-2.256	-2.169	-1.218
5	-3.579	-3.808	-3.747	-2.874	-2.642	-1.796

Surr 17

n	1	2	4	8	16	32
D						
2	-1.167	-1.214	-1.146	-1.097	-0.951	-1.004
3	-2.220	-2.326	-2.318	-2.261	-2.067	-1.704
4	-2.816	-2.812	-3.035	-2.928	-2.710	-2.018
5	-2.929	-2.885	-3.228	-3.024	-2.861	-1.918

Surr 18

n	1	2	4	8	16	32
D						
2	-1.237	-1.178	-1.164	-1.284	-0.963	-0.850
3	-2.450	-2.304	-2.320	-2.375	-1.847	-1.767
4	-2.986	-2.842	-3.052	-2.769	-2.317	-2.352
5	-3.007	-2.896	-3.146	-2.742	-2.400	-2.534

Surr 19

n	1	2	4	8	16	32
D						
2	-1.037	-1.299	-0.723	-1.194	-2.661	-0.870
3	-2.226	-2.604	-1.741	-2.387	-2.365	-1.836
4	-2.971	-3.288	-2.739	-2.961	-1.941	-2.336
5	-3.192	-3.371	-3.437	-2.967	-1.531	-0.365

Surr 20

n	1	2	4	8	16	32
D						
2	-0.711	-1.465	-1.345	-1.119	-1.115	-0.786
3	-1.897	-2.837	-2.573	-2.268	-2.224	-1.673
4	-2.962	-3.482	-3.269	-3.007	-2.776	-2.091
5	-3.733	-3.436	-3.331	-3.160	-2.857	-2.078

Surr 21

n	1	2	4	8	16	32
D						
2	-1.293	-1.153	-1.397	-0.834	-0.767	-0.491
3	-2.462	-2.353	-2.788	-2.063	-1.710	-1.195
4	-3.127	-2.985	-3.435	-2.940	-2.667	-1.954
5	-3.216	-3.127	-3.450	-3.604	-3.346	-2.551

Surr 22

n	1	2	4	8	16	32
D						
2	-1.308	-0.602	-1.417	-1.127	-1.033	-0.644
3	-2.638	-1.748	-2.584	-2.251	-1.971	-1.688
4	-3.384	-2.768	-3.208	-2.837	-2.398	-2.233
5	-3.485	-3.485	-3.227	-2.864	-2.440	-2.230

Surr 23

n	1	2	4	8	16	32
D						
2	-1.333	-1.215	-1.117	-1.234	-0.914	-0.590
3	-2.572	-2.390	-2.400	-2.243	-1.897	-1.078
4	-3.225	-3.047	-2.944	-2.767	-2.435	-1.642
5	-3.201	-3.019	-3.019	-2.862	-2.547	-1.813

Surr 24

n	1	2	4	8	16	32
D						
2	0.160	0.137	-0.174	-0.161	0.139	0.097
3	0.385	0.376	0.075	0.051	0.358	0.307
4	0.547	0.551	0.245	0.239	0.503	0.464
5	0.636	0.672	0.367	0.363	0.623	0.597

Surr 25

n	1	2	4	8	16	32
D						
2	-1.283	-1.125	-0.749	-1.106	-0.999	-0.666
3	-2.450	-2.367	-1.776	-2.133	-2.001	-1.284
4	-3.073	-3.016	-2.663	-2.815	-2.571	-1.617
5	-3.151	-3.043	-3.184	-2.892	-2.649	-1.624

Surr 26

n	1	2	4	8	16	32
D						
2	-0.605	-1.297	-1.217	-1.163	-0.999	-0.751
3	-1.491	-2.548	-2.343	-2.330	-2.077	-1.455
4	-2.524	-3.243	-2.915	-2.926	-2.538	-1.728
5	-3.293	-3.355	-2.959	-3.022	-2.585	-1.695

Surr 27

n	1	2	4	8	16	32
D						
2	-0.792	-1.089	-0.634	-1.094	-0.979	-0.523
3	-1.719	-2.198	-1.560	-2.159	-1.817	-1.452
4	-2.617	-2.841	-2.560	-2.785	-2.318	-1.894
5	-3.234	-2.941	-3.248	-2.806	-2.416	-2.020

Surr 28

n	1	2	4	8	16	32
D						
2	-0.901	-1.241	-1.311	-1.068	-1.322	-1.284
3	-1.994	-2.481	-2.496	-2.315	-2.611	-2.443
4	-2.946	-3.286	-3.211	-3.025	-3.300	-3.007
5	-3.656	-3.414	-3.403	-3.269	-3.430	-3.130

Surr 29

n	1	2	4	8	16	32
D						
2	-0.631	-0.736	-0.769	-1.313	-0.382	-0.354
3	-1.569	-1.921	-1.796	-2.430	-0.965	-0.799
4	-2.647	-3.088	-2.769	-2.932	-1.610	-1.207
5	-3.451	-3.869	-3.406	-2.908	-2.311	-1.694

Surr 30

n	1	2	4	8	16	32
D						
2	-1.093	-1.215	-1.016	-1.054	-1.017	-0.860
3	-2.175	-2.241	-2.584	-2.013	-2.190	-1.694
4	-2.803	-2.801	-2.704	-2.595	-2.812	-2.182
5	-2.912	-2.852	-2.522	-2.613	-2.931	-2.236

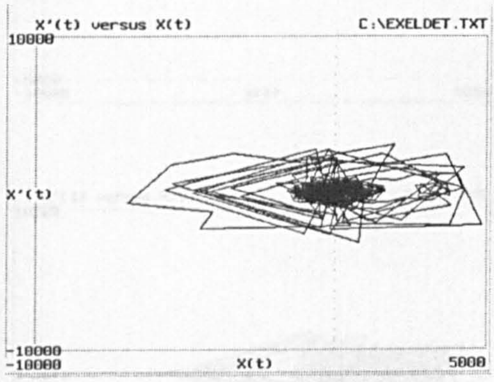
Surr 31

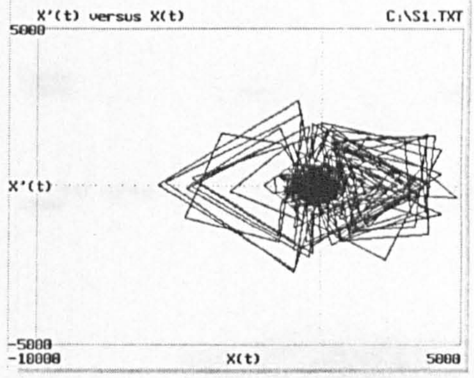
n	1	2	4	8	16	32
D						
2	0.134	-0.200	0.118	0.130	-0.192	0.140
3	0.376	0.014	0.367	0.346	0.036	0.387
4	0.555	0.176	0.557	0.503	0.197	0.459
5	0.665	0.305	0.692	0.612	0.312	0.525

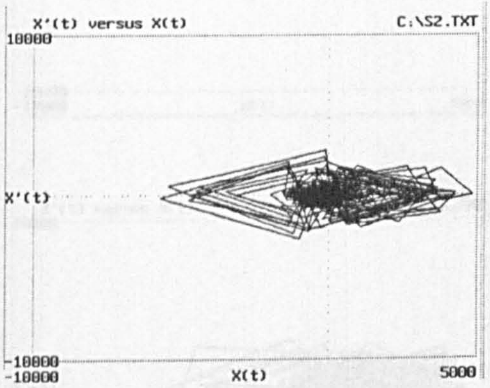
	Surr 32						Surr 33						Surr 34						Surr 35					
n	1	2	4	8	16	32	1	2	4	8	16	32	1	2	4	8	16	32	1	2	4	8	16	32
D																								
2	0.135	0.134	0.141	0.117	-0.220	-0.190	-0.509	-1.319	-1.269	-0.986	-0.573	-0.991	0.137	0.129	0.094	0.115	-0.221	0.127	-1.337	-1.220	-0.656	-1.137	-0.997	-0.942
3	0.389	0.373	0.348	0.347	0.029	0.065	-1.532	-2.540	-2.397	-2.162	-1.504	-2.033	0.382	0.356	0.309	0.335	0.023	0.412	-2.502	-2.484	-1.506	-2.356	-2.141	-1.936
4	0.520	0.519	0.462	0.507	0.188	0.299	-2.633	-3.167	-3.034	-2.830	-2.390	-2.352	0.542	0.493	0.470	0.494	0.180	0.560	-3.125	-3.262	-2.486	-3.195	-2.744	-2.313
5	0.601	0.617	0.575	0.622	0.330	0.447	-3.387	-3.184	-3.178	-2.970	-3.242	-2.316	0.668	0.605	0.590	0.590	0.031	0.698	-3.217	-3.325	-3.337	-3.333	-2.889	-2.261

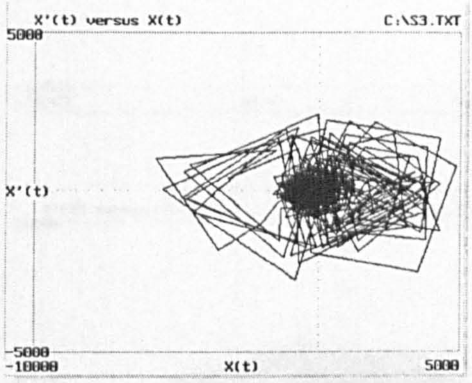
	Surr 36						Surr 37						Surr 38						Surr 39					
n	1	2	4	8	16	32	1	2	4	8	16	32	1	2	4	8	16	32	1	2	4	8	16	32
D																								
2	0.137	0.100	0.112	0.129	0.084	0.115	0.095	-0.198	-0.178	-0.181	-0.187	0.154	0.151	0.143	0.128	0.131	-0.184	-0.112	0.132	-0.176	0.158	0.106	0.106	0.108
3	0.350	0.328	0.355	0.376	0.310	0.300	0.340	0.023	0.034	0.056	0.086	0.431	0.395	0.391	0.375	0.355	0.046	0.084	0.334	0.023	0.374	0.365	0.318	0.330
4	0.468	0.491	0.502	0.538	0.430	0.445	0.502	0.198	0.201	0.238	0.243	0.575	0.553	0.547	0.506	0.508	0.194	0.256	0.499	0.176	0.505	0.515	0.414	0.451
5	0.570	0.595	0.609	0.686	0.541	0.513	0.632	0.313	0.327	0.355	0.340	0.721	0.672	0.632	0.618	0.655	0.301	0.367	0.596	0.295	0.601	0.622	0.547	0.569

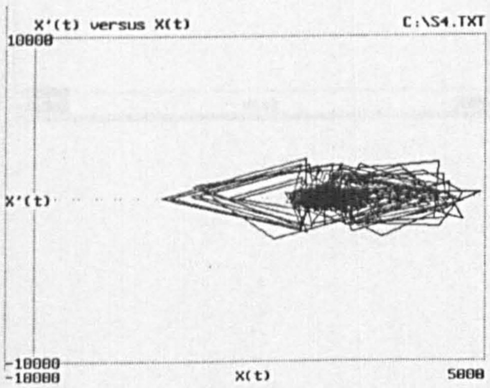
Appendix 7: Phase Space for AFFT Surrogate Data

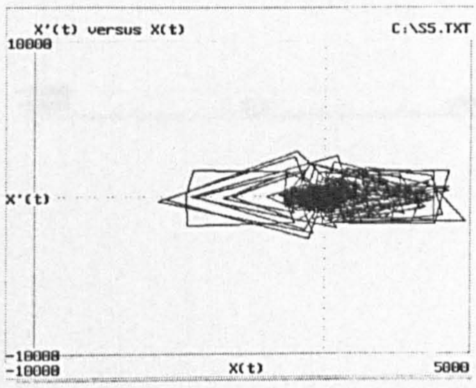


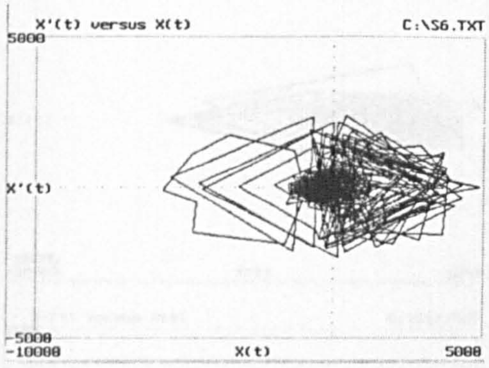








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X'(t)
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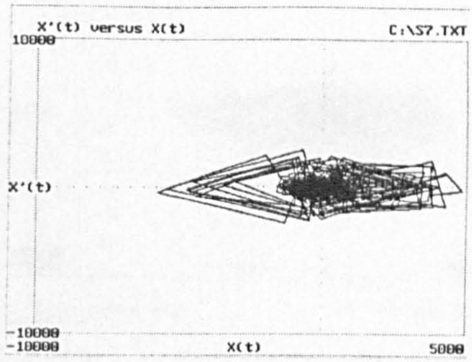
X(t)
5000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X'(t)
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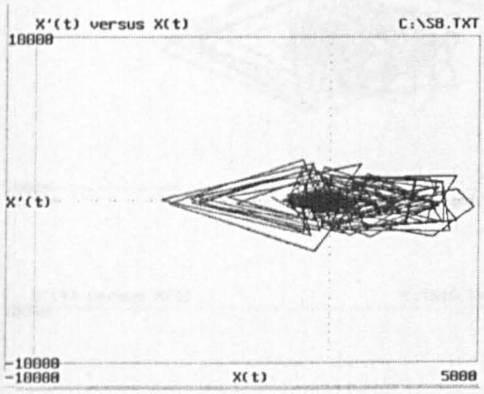
X(t)
5000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X'(t)
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-10000
X(t)
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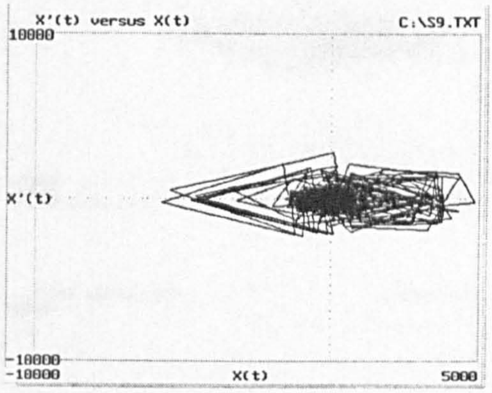
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X'(t)
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-10000
X(t)
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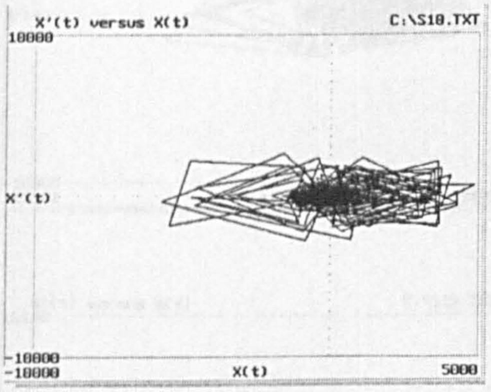
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X(t)
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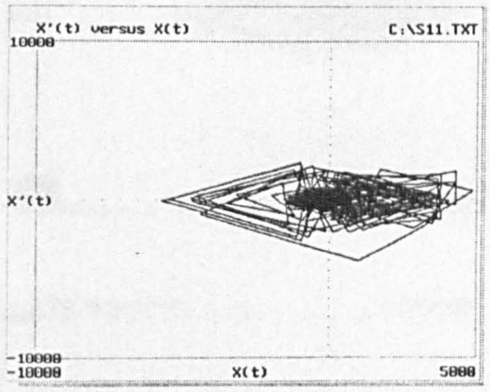
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X'(t)
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X(t)
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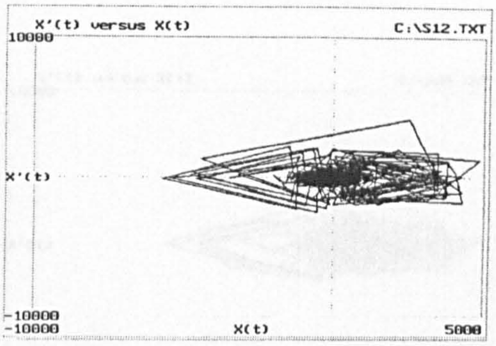
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X'(t)
-10000
-10000
X(t)
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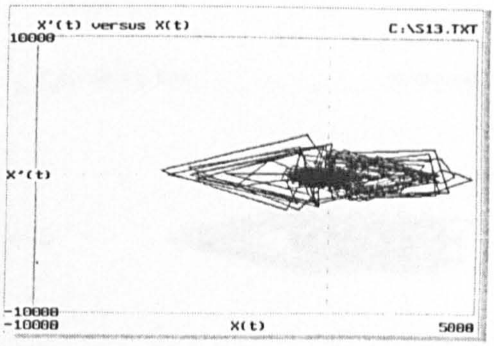
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X'(t)
-10000
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X(t)
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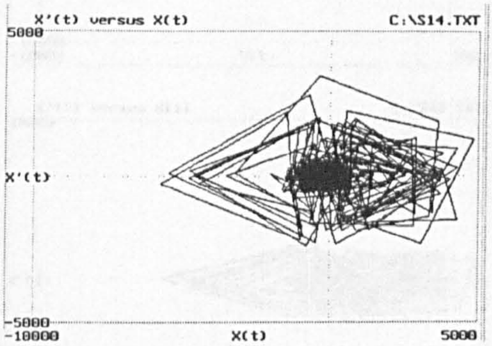
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X(t)
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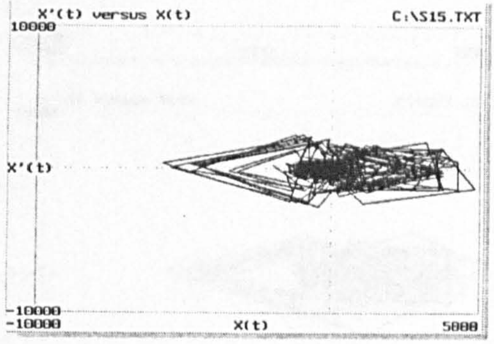
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X'(t)
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X(t)
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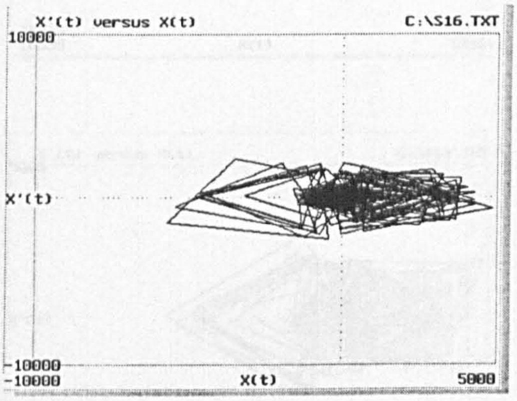
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X'(t)
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X(t)
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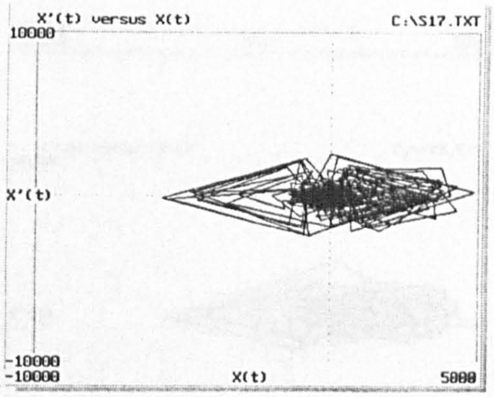
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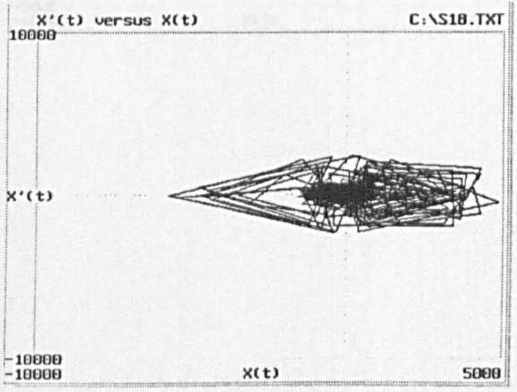
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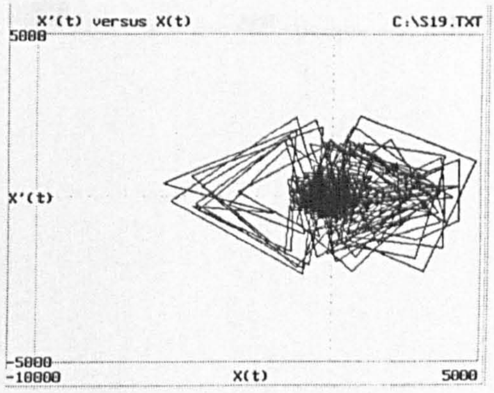
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X(t)
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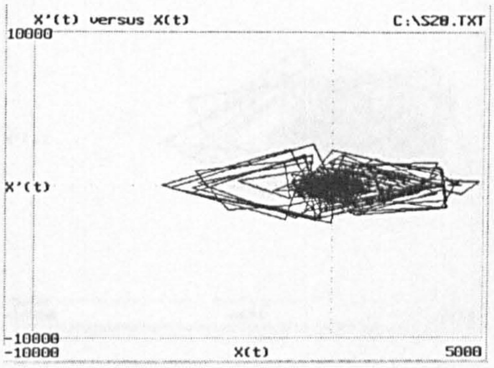
X'(t) versus X(t)
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X'(t)
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X(t)
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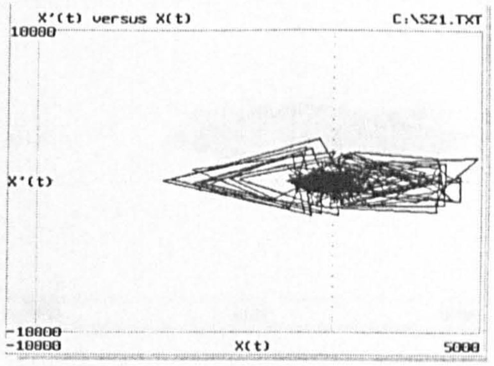
X'(t) versus X(t)
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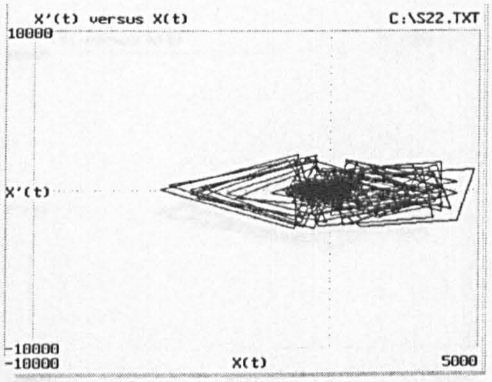
X'(t)
-10000
-10000
X(t)
5000


X'(t) versus X(t)
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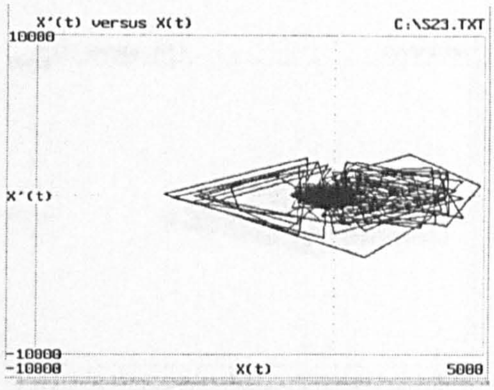
X'(t)
-10000
-10000
X(t)
5000


X'(t) versus X(t)
C:\S23.TXT
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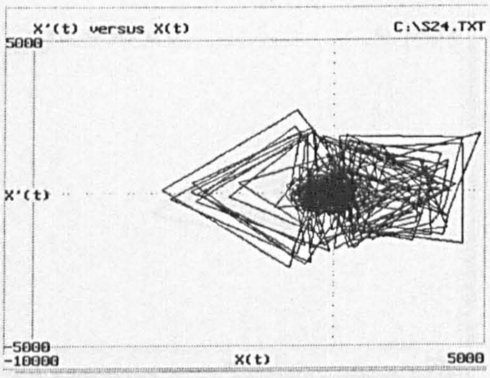
X'(t)
-10000
-10000
X(t)
5000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X(t)
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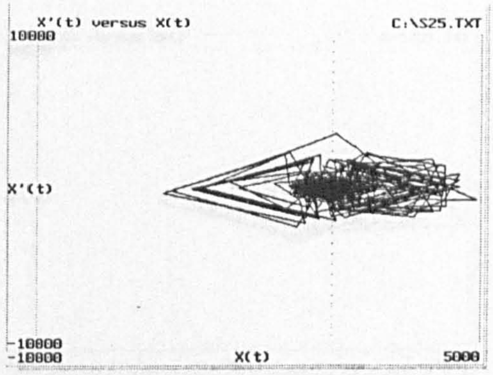
X'(t) versus X(t)
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X'(t)
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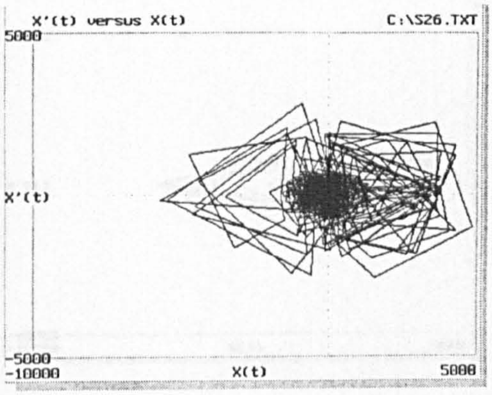
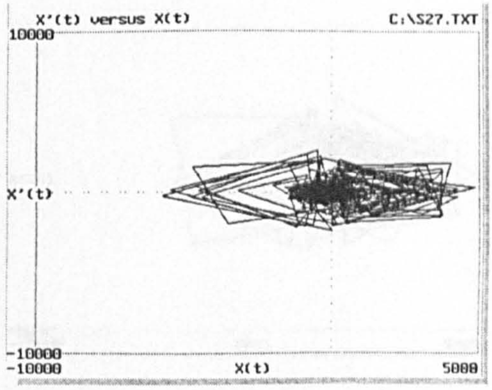
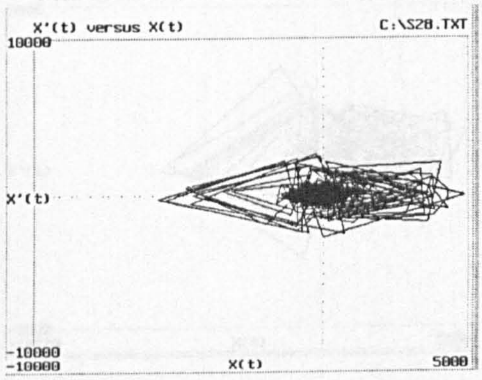
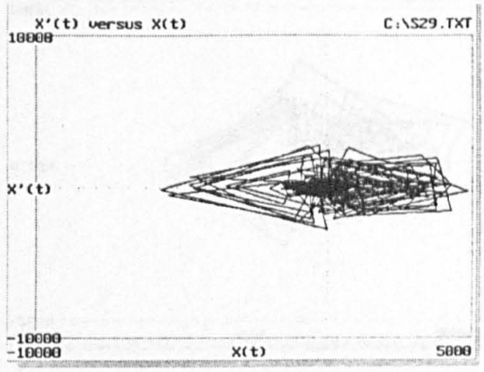
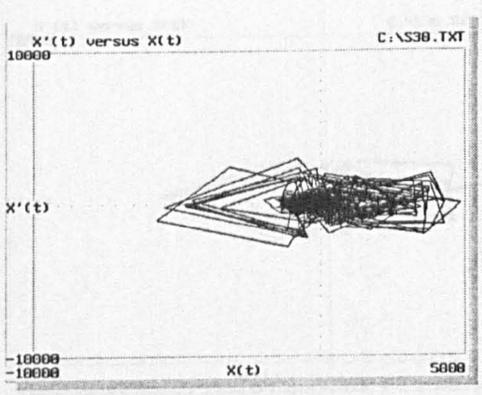
X(t)
5000

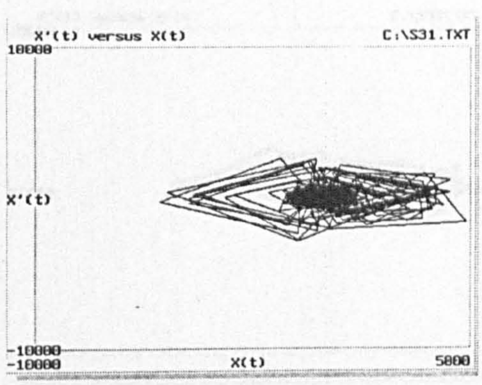

X'(t) versus X(t)
C:\S26.TXT
5000
X'(t)
-5000
-10000
X(t)
5000

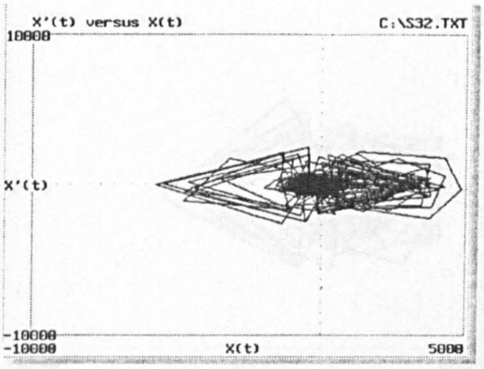
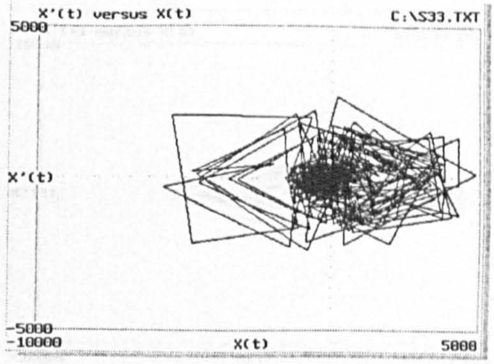
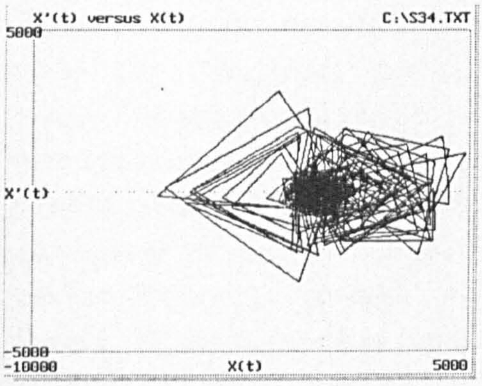
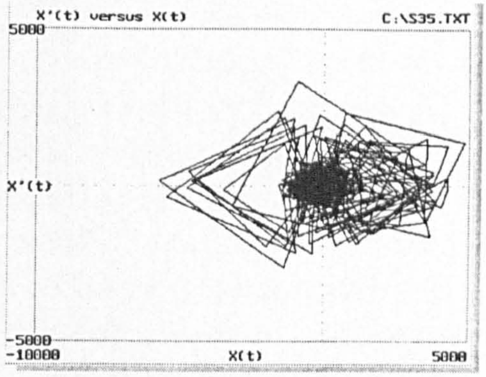
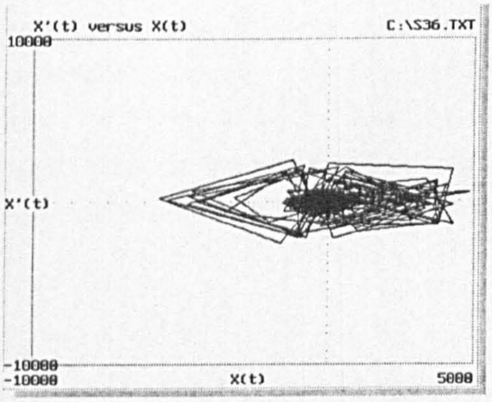
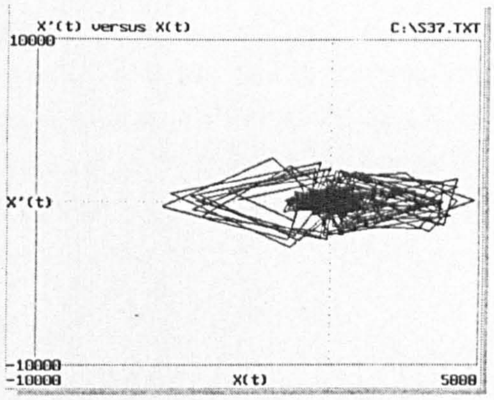

X'(t) versus X(t)
C:\S27.TXT
10000
X'(t)
-10000
-10000
X(t)
5000

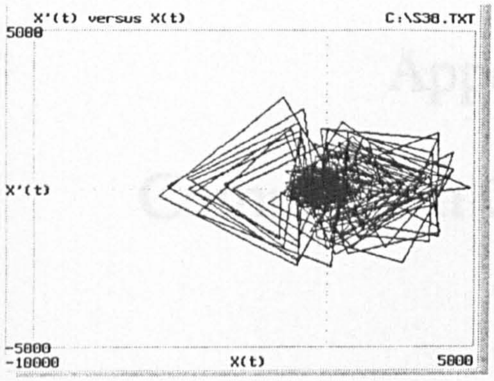

X'(t) versus X(t)
C:\S28.TXT
10000
X'(t)
-10000
-10000
X(t)
5000

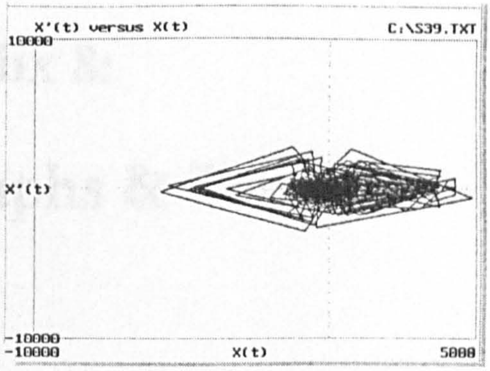

X'(t) versus X(t)
C:\S29.TXT
10000
X'(t)
-10000
-10000
X(t)
5000


X'(t) versus X(t)
C:\S30.TXT
10000
X'(t)
-10000
-10000
X(t)
5000


X'(t) versus X(t)
C:\S31.TXT
10000
X'(t)
-10000
-10000
X(t)
5000


X'(t) versus X(t)
C:\S32.TXT
10000
X'(t)
-10000
-10000
X(t)
5000

X'(t) versus X(t)
C:\S33.TXT
5000
X'(t)
-5000
-10000
X(t)
5000

X'(t) versus X(t)
C:\S34.TXT
5000
X'(t)
-5000
-10000
X(t)
5000

X'(t) versus X(t)
C:\S35.TXT
5000
X'(t)
-5000
-10000
X(t)
5000

X'(t) versus X(t)
C:\S36.TXT
10000
X'(t)
-10000
-10000
X(t)
5000

X'(t) versus X(t)
C:\S37.TXT
10000
X'(t)
-10000
-10000
X(t)
5000


X'(t) versus X(t)
C:\S38.TXT
5000
X'(t)
-5000
-10000
X(t)
5000

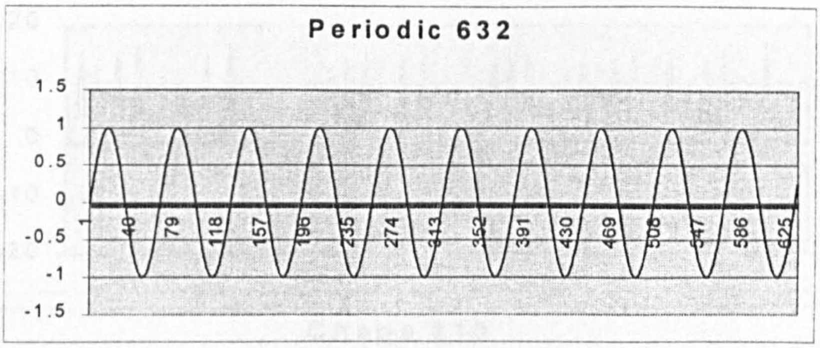

X'(t) versus X(t)
C:\S39.TXT
10000
X'(t)
-10000
-10000
X(t)
5000

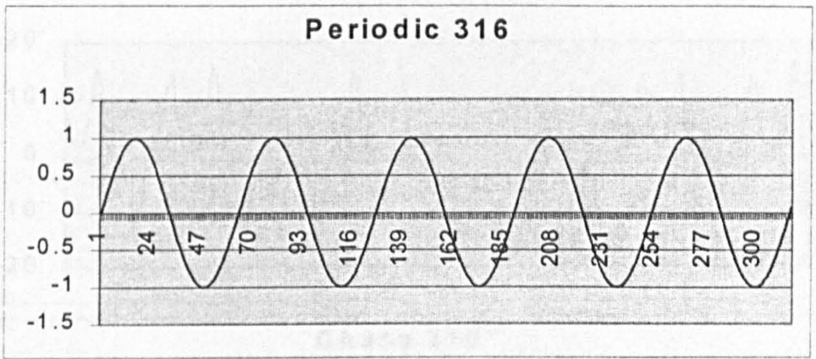
Appendix 8:

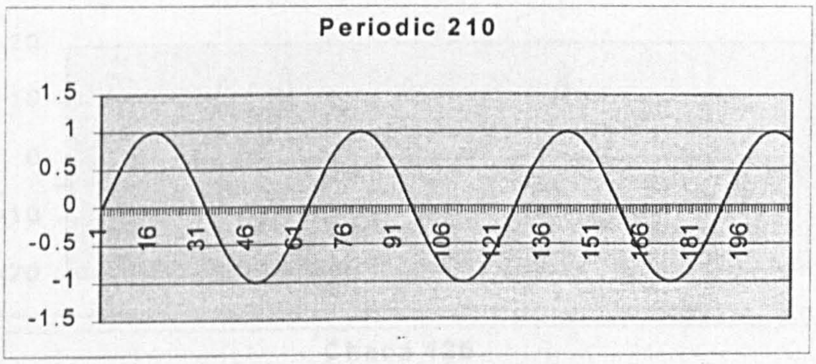
Comparison Graphs & Tables

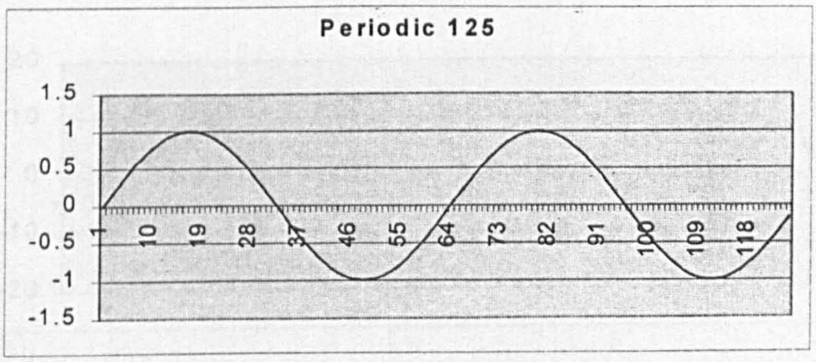
The purpose of this appendix is to provide evidence that the analysis of CASTS method gives valid results when it is applied on experimental periodic, chaotic and random data sets for the same number of data points -632, 316, 210, and 125- as those of the real data sets analysed in this thesis. Because the purpose of this thesis is not to construct new equations for chaotic analysis but rather to compose a new methodology for logistics demand analysis based on already proven equations, a selection of the most important CASTS tests was made from the author. This also allows a fast and easy way to compare the experimental with the real data results. However, it has to be mentioned that a more detailed presentation and explanation of the results that each of the CASTS' techniques provide is widely covered from current literature, the most important references of which can be found in Chapter 4 under the subsection of each particular test. Finally, it has to be mentioned that the some of the techniques results are influenced from the number of the data points used. More in depth discussion about this issue can also be found in Chapter 4 in the section about the CASTS limitations and each technique's relevant subsection.

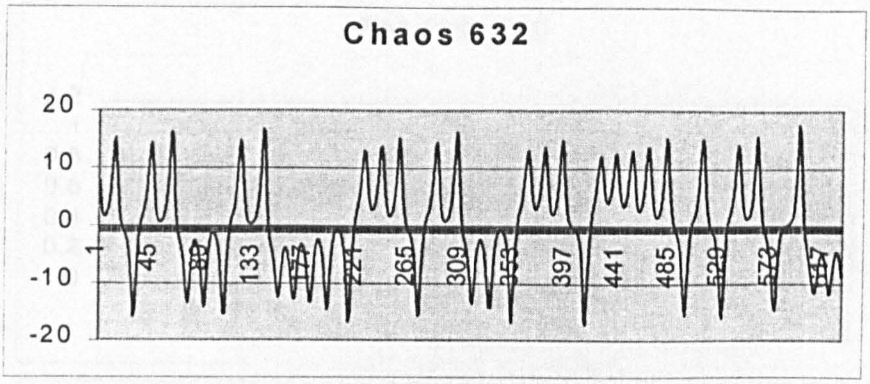
Pseudo & Phase Space Plots

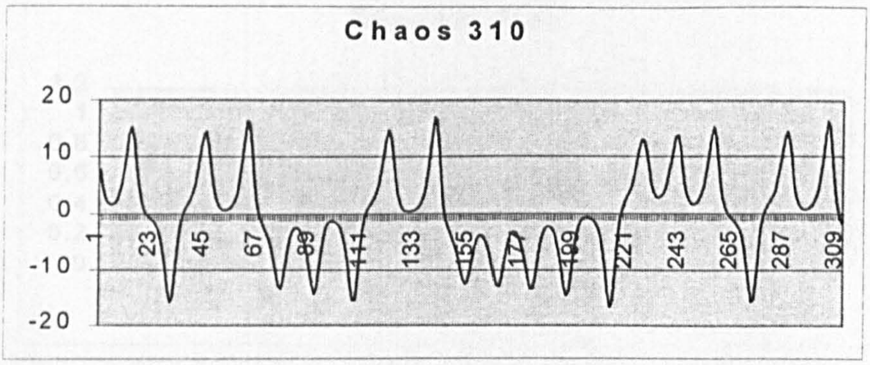


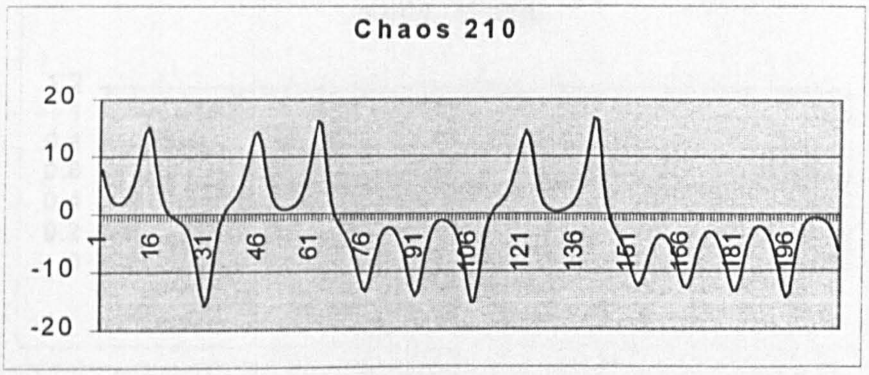


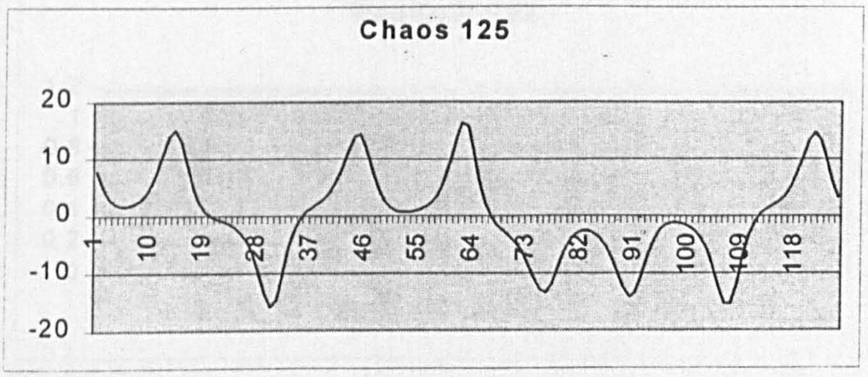


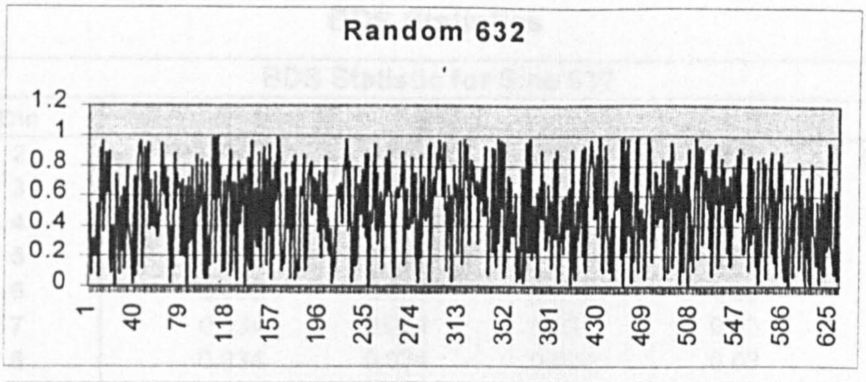


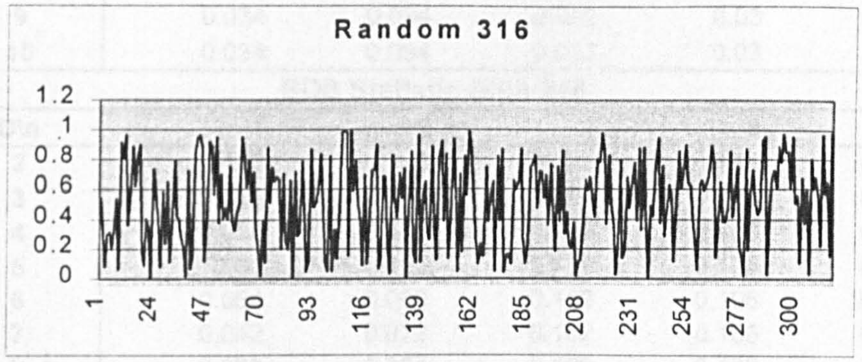

Chaos 632
20
10
0
-10
-20
1
45
89
133
177
221
265
309
353
397
441
485
529
573
617

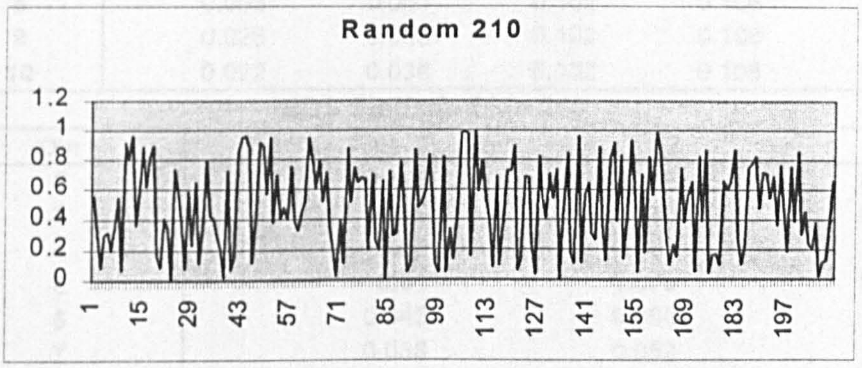

Chaos 310
20
10
0
-10
-20
1
23
45
67
89
111
133
155
177
199
221
243
265
287
309

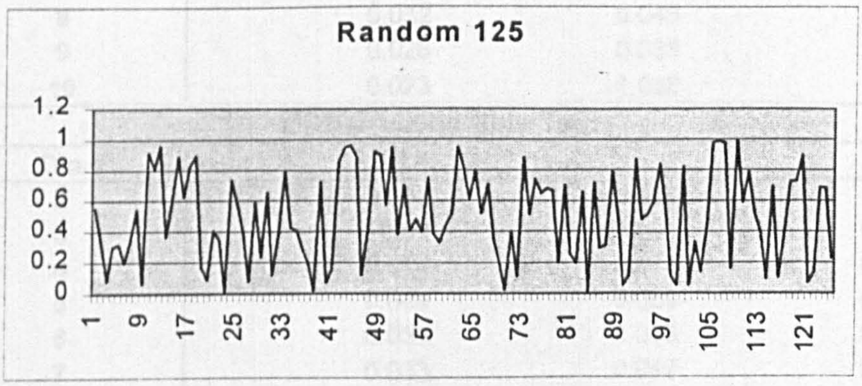

Chaos 210
20
10
0
-10
-20
1
16
31
46
61
76
91
106
121
136
151
166
181
196


Chaos 125
20
10
0
-10
-20
1
10
19
28
37
46
55
64
73
82
91
100
109
118


Random 632
1.2
1
0.8
0.6
0.4
0.2
0
1 40 79 118 157 196 235 274 313 352 391 430 469 508 547 586 625


Random 316
1.2
1
0.8
0.6
0.4
0.2
0
1 24 47 70 93 116 139 162 185 208 231 254 277 300


Random 210
1.2
1
0.8
0.6
0.4
0.2
0
1 15 29 43 57 71 85 99 113 127 141 155 169 183 197


Random 125
1.2
1
0.8
0.6
0.4
0.2
0
1 9 17 25 33 41 49 57 65 73 81 89 97 105 113 121

BDS Statistics

BDS Statistic for Sine 632					
D\n	1	2	4	8	16
2	0.047	0.039	0.032	0.029	0.208
3	0.039	0.034	0.032	0.03	0.23
4	0.034	0.034	0.032	0.03	0.15
5	0.034	0.034	0.032	0.03	0
6	0.035	0.034	0.032	0.03	0.15
7	0.034	0.034	0.032	0.03	0.15
8	0.034	0.034	0.032	0.03	0.15
9	0.034	0.034	0.032	0.03	0.15
10	0.034	0.034	0.032	0.03	0.15

BDS Statistic Sine 316					
D\n	1	2	4	8	16
2	0.183	0	0.238	0.18	0.112
3	0.126	0.208	0.191	0.151	0.135
4	0.094	0.172	0.149	0.106	0.112
5	0.07	0.125	0.129	0.106	0.112
6	0.054	0.089	0.102	0.106	0.112
7	0.042	0.072	0.102	0.106	0.112
8	0.033	0.051	0.102	0.106	0.112
9	0.026	0.045	0.102	0.106	0.112
10	0.022	0.038	0.102	0.106	0.112

BDS Statistic Sine 210			
D\n	1	2	4
2	0.126	0.166	0.167
3	0.088	0.141	0.141
4	0.66	0.101	0.13
5	0.51	0.079	0.124
6	0.043	0.066	0.17
7	0.038	0.052	0.17
8	0.032	0.045	0.17
9	0.026	0.038	0.17
10	0.023	0.028	0.17

BDS Statistic Sine 125			
D\n	1	2	4
2	0.097	0.096	0
3	0.07	0.091	0.062
4	0.054	0.071	0.063
5	0.044	0.059	0.063
6	0.039	0.053	0.063
7	0.033	0.049	0.063
8	0.03	0.045	0.063
9	0.026	0.041	0.063
10	0.023	0.032	0.063

BDS Statistic for Chaos 632					
D\n	1	2	4	8	16
2	0.7	0.609	0.344	0.157	-0.74
3	0.473	0.444	0.591	0.327	-0.747
4	0.286	0.265	0.456	0.194	-0.643
5	0.179	0.172	0.294	0.166	-0.57
6	0.118	0.122	0.182	0.115	-0.531
7	0.084	0.089	0.132	0.074	-0.479
8	0.064	0.064	0.095	0.049	-0.422
9	0.05	0.047	0.066	0.034	-0.36
10	0.042	0.033	0.047	0.023	-0.286

BDS Statistic Chaos 316					
D\n	1	2	4	8	16
2	0.317	0.254	0.583	-1.442	-0.246
3	0.195	0.161	0.566	-1.453	-0.235
4	0.113	0.101	0.598	-1.454	-0.122
5	0.072	0.073	0.56	-1.33	-0.069
6	0.051	0.055	0.41	-0.871	-0.116
7	0.036	0.041	0.63	-0.626	-0.207
8	0.029	0.03	0.941	-0.435	-0.271
9	0.023	0.024	0.981	-0.3	-0.244
10	0.98	0.019	0.981	-0.206	-0.167

BDS Statistic Chaos 210					
D\n	1	2	4	8	16
2	0.02	0.015	0.111	0.02	0.25
3	0	0	0.324	0	0.468
4	0.416	0.36	0.325	-0.396	0.535
5	0.278	0.265	0.234	-0.318	0.486
6	0.166	0.159	0.152	-0.335	0.265
7	0.098	0.103	0.118	-0.139	0.149
8	0.064	0.071	0.093	-0.034	0.06
9	0.042	0.047	0.068	0.04	0.045
10	0.03	0.033	0.046	0.052	0.03

BDS Statistic Chaos 125					
D\n	1	2	4	8	16
2		0.509	0.366	-0.662	0
3		0.341	0.277	-0.971	0
4		0.221	0.175	-0.708	0
5		0.14	0.107	-0.423	0
6		0.084	0.069	-0.353	0
7		0.056	0.04	-0.306	0
8		0.033	0.032	-0.192	0
9		0.018	0.024	-0.128	0
10		0.012	0.018	-0.123	0

BDS Statistic for Random 632					
D\n	1	2	4	8	16
2	-1.991	-1.947	-1.947	-1.636	-1.636
3	-4.825	-4.764	-4.783	-4.528	-4.069
4	-7.484	-7.429	-7.461	-7.058	-6.403
5	-9.459	-9.426	-9.377	-8.959	-8.15
6	-10.589	-10.541	-10.453	-10.07	-9.15
7	-10.97	-10.896	-10.796	-10.454	-9.5
8	-10.813	-10.762	-10.64	-10.35	-9.364
9	-10.347	-10.303	-10.187	-9.94	-8.964
10	-9.709	-9.666	-9.567	-9.353	-8.426

BDS Statistic Random 316					
D\n	1	2	4	8	16
2	-1.341	-1.294	-1.413	-1.176	-1.086
3	-3.306	-2.505	-2.553	-2.553	-2.57
4	-5.203	-3.081	-3.028	-3.028	-3.607
5	-6.634	-3.64	-3.64	-2.967	-4.749
6	-7.53	-2.669	-2.967	-2.609	-4.836
7	-7.92	-2.206	-2.609	-2.173	-4.749
8	-7.858	-1.757	-1.757	-1.742	-4.664
9	-7.581	-1.371	-1.371	-1.362	-4.407
10	-7.167	-1.057	-1.057	-1.059	-4.119

BDS Statistic Random 210					
D\n	1	2	4	8	16
2	-1.169	-0.982	-1.145	-0.989	-0.46
3	-2.805	-1.826	2.752	-2.302	-1.052
4	-4.251	-2.175	-4.048	-3.502	-1.449
5	-5.277	-2.081	-4.888	-4.311	-1.765
6	-5.823	-1.767	-5.279	-4.739	-1.986
7	-5.991	-1.416	-5.319	-4.837	-2.056
8	-5.858	-1.091	-5.181	-4.727	-2.012
9	-5.565	-0.812	-4.906	-4.489	-1.88
10	-5.179	-0.602	-4.549	-4.153	-1.715

BDS Statistic Random 125				
D\n	1	2	4	8
2	-0.909	-0.923	-0.746	-0.623
3	-2.101	-2.137	-1.285	-1.223
4	-3.147	-3.26	-1.497	-1.702
5	-3.916	-4.065	-1.493	-2.075
6	-4.367	-4.501	-1.325	-2.198
7	-4.527	-4.609	-1.084	-2.211
8	-4.435	-4.535	-0.837	-2.077
9	-4.213	-4.32	-0.638	-1.946
10	-3.921	-4.032	-0.486	-1.78

Correlation Dimension

	Correlation Dimension for Periodic 632											
	1		2		4		8		16		32	
	CorDim	± error	CorDim	± error	CorDim	± error	CorDim	± error	CorDim	± error	CorDim	± error
2	0.924	0.815	0.985	0.616	1.2	0.389	1.565	0.715	3.524	1.736	1.454	0.176
3	0.883	0.548	1.058	0.444	1.331	0.365	2.156	1.726	2.001	1.86	1.541	0.219
4	0.984	0.68	1.187	0.578	1.475	0.683	4.64	2.849	3.524	1.736	1.593	0.227
5	0.98	0.78	1.319	0.622	1.8	0.724	2.942	1.56	3.524	1.736	1.715	444
6	1.017	0.448	1.317	0.571	2.186	1.702	2.334	1.929	3.524	1.736	1.794	0.365
7	1.172	0.486	1.481	0.748	2.848	3.263	2.885	3.27	1.948	1.59	1.678	0.54
8	1.176	0.653	1.454	0.646	4.598	2.851	4.64	2.849	3.529	1.736	1.742	0.507
9	1.37	0.471	1.739	0.99	2.449	1.873	2.506	1.911	3.524	1.736	1.796	0.407
10	1.316	0.702	1.762	0.723	2.935	1.5	2.954	1.56	3.524	1.736	1.84	0.34

	Correlation Dimension for Periodic 316									
	1		2		4		8		16	
	CorDim	± error	CorDim	± error	CorDim	± error	CorDim	± error	CorDim	± error
2	1.505	0.107	1.588	0.217	1.904	0.63	4.113	3.386	4.113	3.286
3	1.609	0.122	1.707	0.514	1.874	0.692	2.369	3.204	2.369	3.576
4	1.611	0.287	1.831	0.421	1.986	1.143	4.113	3.271	4.113	3.286
5	1.774	0.219	2.061	1.136	3.263	3.097	4.113	3.271	4.113	3.286
6	1.706	0.616	1.956	0.728	2.755	3.137	2.962	3.268	2.962	3.368
7	1.809	0.688	2.882	3.241	2.905	3.214	2.167	3.303	2.167	3.51
8	1.853	0.438	2.081	1.221	4.597	2.802	4.113	3.271	4.113	3.286
9	1.797	0.61	3.154	3.123	4.597	2.802	4.113	3.271	4.113	3.286
10	2.17	1.341	3.293	3.031	4.597	2.802	2.962	3.271	2.962	3.368

	Correlation Dimension for Periodic 210							
	1		2		4		8	
	CorDim	± error	CorDim	± error	CorDim	± error	CorDim	± error
2	1.404	0.191	1.536	0.531	1.646	0.99	2.626	3.615
3	1.411	0.571	1.639	0.866	2.469	3.489	2.354	3.615
4	1.525	0.268	1.819	1.407	2.754	3.533	3.783	3.615
5	1.503	0.477	1.842	1.262	2.436	3.475	2.841	3.615
6	1.543	0.61	2.546	3.478	2.347	3.6	2.158	3.615
7	1.683	0.731	2.646	3.544	2.184	3.514	2.471	3.615
8	1.96	1.667	2.537	3.518	4.21	3.188	3.783	3.615
9	1.636	0.7	2.444	3.375	4.21	3.188	2.939	3.615
10	1.935	1.36	2.557	3.458	4.21	3.188	2.777	3.615

	Correlation Dimension for Periodic 125							
	1		2		4		8	
	CorDim	± error	CorDim	± error	CorDim	± error	CorDim	± error
2	1.297	0.466	1.26	0.752	1.308	1.292	9.393	9.398
3	1.185	0.566	1.255	0.851	2.399	3.404	-	-
4	1.211	0.441	1.274	0.939	3.824	3.19	-	-
5	1.18	0.675	1.528	1.971	2.947	3.632	-	-
6	1.295	0.958	2.454	3.385	2.667	3.398	-	-
7	1.261	0.927	2.478	3.535	3.872	2.661	-	-
8	1.432	1.589	3.297	3.274	4.771	2.628	-	-
9	2.104	3.457	2.291	3.628	4.476	2.922	-	-
10	1.465	1.52	2.906	3.473	4.303	3.096	-	-

	Correlation Dimension for Chaos 632											
	1		2		4		8		16		32	
	CorDim	± error	CorDim	± error	CorDim	± error	CorDim	± error	CorDim	± error	CorDim	± error
2	1.95	0.205	2.015	0.241	1.852	0.168	1.954	0.31	1.835	0.352	6.433	6.433
3	2.052	1.188	2.183	0.187	2.028	0.126	2.191	0.103	2.002	0.126	1.023	0.257
4	2.105	1.198	2.112	0.177	2.105	0.17	2.029	0.222	2.077	0.296	1.793	0.23
5	2.15	1.189	2.074	0.113	2.075	0.087	2.083	0.151	2.312	0.679	1.99	0.362
6	2.245	0.25	2.186	0.354	1.963	0.066	2.132	0.244	2.82	0.614	3.066	0.44
7	2.108	0.065	2.114	0.239	1.957	0.186	2.05	0.387	3.91	0.323	4.547	0.536
8	2.159	0.19	2.125	0.247	1.926	0.315	2.034	0.51	4.531	4.531	4.828	0.344
9	2.058	0.039	2.12	0.225	2.039	0.235	2.187	0.236	5.173	0.309	6.503	6.503
10	2.084	0.096	2.143	0.204	2.117	0.221	2.261	0.287	5.608	5.608	6.72	0.629

	Correlation Dimension for Chaos 316									
	1		2		4		8		16	
	CorDim	± error	CorDim	± error	CorDim	± error	CorDim	± error	CorDim	± error
2	1.95	0.39	2.186	1.717	1.618	0.317	1.942	0.328	2.532	0.799
3	2.029	0.163	1.805	0.267	1.968	0.189	2.675	0.813	2.757	0.883
4	2.007	0.576	1.99	0.247	2.076	0.548	2.577	0.931	2.819	0.907
5	1.998	0.306	2.067	0.373	1.805	0.354	2.837	0.779	2.551	0.877
6	1.994	0.221	1.908	0.328	1.836	0.614	3.689	0.964	5.798	5.798
7	1.944	0.259	1.915	0.605	2.026	1.578	3.4	1.283	6.525	0.873
8	1.944	0.395	2.161	1.06	1.643	1.713	4.028	1.969	5.847	0.333
9	1.955	0.5	1.855	0.557	1.749	1.019	3.125	0.622	6.218	6.218
10	2.138	0.903	1.942	0.779	2.115	1.285	3.205	0.462	6.356	1.043

	Correlation Dimension for Chaos 210									
	1		2		4		8		16	
	CorDim	± error	CorDim	± error	CorDim	± error	CorDim	± error	CorDim	± error
2	2.256	0.318	2.577	0.403	2.227	0.761	2.662	0.333	3.949	3.096
3	2.584	0.607	2.673	0.288	2.631	0.156	2.364	0.555	4.737	2.661
4	2.547	0.761	2.938	0.617	2.307	1.151	2.377	0.852	4.158	2.661
5	2.443	0.379	2.84	0.553	2.985	1.34	2.357	0.539	5.525	1.873
6	2.401	0.106	2.649	0.317	3.658	2.81	3.568	1.798	6.144	1.254
7	2.536	0.254	2.811	0.134	2.929	1.566	4.755	2.52	7.398	7.398
8	2.539	0.115	2.791	0.694	3.493	1.794	4.805	1.849	7.398	7.398
9	2.421	0.181	2.52	0.729	2.961	0.518	4.401	2.279	7.398	7.398
10	2.474	0.239	2.519	0.896	4.177	1.203	3.447	0.265	7.398	7.398

	Correlation Dimension for Chaos 125							
	1		2		4		8	
	CorDim	± error	CorDim	± error	CorDim	± error	CorDim	± error
2	2.322	0.228	3.235	0.421	2.732	1.666	4.488	2.661
3	2.439	0.403	3.765	0.589	3.682	1.501	4.239	2.661
4	2.401	0.997	4.619	1.635	4.117	2.589	5.065	2.334
5	2.965	0.043	3.469	0.52	4.139	6.751	6.643	6.755
6	3.329	0.087	3.96	2.661	5.694	1.705	7.398	7.398
7	3.956	1.475	3.846	2.936	5.094	5.094	-	-
8	3.744	0.67	3.883	2.809	4.826	1.174	7.398	7.398
9	3.676	0.957	2.723	1.391	6.258	1.141	7.398	7.398
10	4.004	1.293	3.439	3.153	6.006	1.392	-	-

	Correlation Dimension for Random632											
	1		2		4		8		16		32	
	CorDim	±error	CorDim	±error	CorDim	±error	CorDim	±error	CorDim	±error	CorDim	±error
2	2.068	0.048	2.175	0.211	2.081	0.11	2.022	0.213	2.039	0.062	2.003	0.405
3	3.053	0.015	2.907	0.02	3.129	0.047	2.837	0.011	2.796	0.102	3.011	0.306
4	3.745	0.023	3.601	0.102	3.774	0.133	3.821	0.101	3.942	0.098	3.762	0.241
5	4.563	4.563	4.101	-	4.282	0.156	4.478	0.083	4.331	0.182	4.618	-
6	4.969	-	5.069	-	4.68	-	5.284	-	5.081	5.081	4.763	-
7	5.242	0.94	5.549	0.132	5.385	0.163	5.958	0.341	5.345	0.334	5.371	0.188
8	5.689	-	5.793	-	5.64	-	6.051	-	6.184	-	5.765	-
9	5.721	-	6.149	-	6.156	-	6.242	-	6.502	-	6.195	-
10	6.429	-	6.175	-	6.226	-	6.444	-	6.381	-	6.345	-

	Correlation Dimension for Random 316									
	1		2		4		8		16	
	CorDim	± error	CorDim	± error	CorDim	± error	CorDim	± error	CorDim	± error
2	1.898	0.249	2.147	0.398	2.062	0.234	1.89	0.325	2.095	0.572
3	2.762	0.13	3.042	0.051	3.718	0.15	2.319	0.896	2.61	0.262
4	3.937	0.262	3.909	0.277	3.929	0.236	4.063	0.389	4.477	1.109
5	4.572	4.572	4.214	4.214	4.479	4.479	4.198	-	4.399	-
6	5.707	5.707	5.615	-	5.271	0.451	5.347	-	4.321	-
7	5.83	0.513	5.959	0.343	5.441	0.281	6.21	0.781	6.29	-
8	5.798	5.798	6.153	-	5.551	-	5.817	-	7.023	-
9	6.191	6.191	6.153	-	6.6	-	6.377	-	7.98	-
10	6.375	6.375	6.5	0.482	6.285	0.29	6.733	0.665	7.161	-

	Correlation Dimension for Random 210									
	1		2		4		8		16	
	CorDim	± error	CorDim	± error	CorDim	± error	CorDim	± error	CorDim	± error
2	1.752	0.339	2.147	0.314	1.811	0.262	1.909	0.419	4.706	2.334
3	2.639	0.238	3.398	0.591	2.977	0.507	3.11	1.256	5.32	2.078
4	4.037	0.079	3.782	0.363	3.53	0.594	4.086	1.56	4.581	2.661
5	4.752	0.195	4.158	0.653	4.201	0.434	3.446	0.258	6.407	0.992
6	5.668	5.668	5.675	5.675	4.826	0.589	4.444	4.444	-	-
7	5.461	6.476	6.021	0.498	5.235	1.618	5.581	0.307	7.398	-
8	4.914	4.914	5.889	5.889	5.757	1.641	5.965	5.965	7.398	-
9	5.603	5.603	6.453	6.453	4.822	4.822	6.428	0.97	-	-
10	6.289	6.289	6.331	1.068	5.769	5.769	6.519	6.519	-	-

	Correlation Dimension for Random 125							
	1		2		4		8	
	CorDim	± error	CorDim	± error	CorDim	± error	CorDim	± error
2	1.901	0.591	2.34	0.88	1.961	1.017	2.416	3.274
3	3.07	0.703	3.197	0.465	2.375	0.962	3.53	3.169
4	3.467	0.87	4.185	0.323	4.119	0.877	4.354	2.862
5	4.419	0.283	4.611	0.102	4.969	1.127	6.643	6.755
6	5.362	5.362	4.648	4.648	4.89	4.89	7.398	7.398
7	5.435	0.168	5.793	5.793	5.848	1.55	5.834	1.564
8	4.89	4.89	4.182	4.182	5.86	1.53	5.953	1.445
9	7.398	7.398	3.242	3.242	5.525	1.873	7.398	7.398
10	7.105	7.105	5.858	5.85	4.397	0.408	7.398	7.398

Lyaponov Exponent

Periodic 632 0 ±0.012	Chaos 632: 0.121±0.056	Random 632: 0.883±0.059
Periodic 316 0±0.065	Chaos 316: 0.082±0.023	Random 316: 0.878±0.081
Periodic 210: -0.011±0.081	Chaos 210: 0.140±0.098	Random 210: 0.867±0.099
Periodic 125: 0.012±0.111	Chaos 125: 0.181±0.094	Random 125: 0.666±0.175

Hurst Exponent

	Hurst Exponent
Periodic 632	0.912
Chaos 632	0.516
Random 632	2.745E-4
Periodic 316	0.946
Chaos 316	0.524
Random 316	-9.850E-3
Periodic 210	0.969
Chaos 210	0.610
Random 210	1.529E-3
Periodic 125	0.965
Chaos 125	0.683
Random 125	3.282E-2

Glossary

Glossary

Antipersistence An antipersistent time series reverses itself more often than a random series would. If the system had been up in the previous period, it is more likely that it will be down in the next period and vice versa.

Aperiodic It is a behaviour, which is not repeated with time.

Attractor It is a point of attraction (basin) towards which a time series (or a set of points) converge in phase space. The attractor defines the equilibrium level of the system.

Autocorrelation It measures the dependencies between the values of a time series at a certain distance apart.

BDS Statistics A statistic based on the correlation integral that examines the probability that a purely random system could have the same scaling properties as the system under study. Named after the inventors of the method: Brock, Dechert, and Scheinkman (1987).

Bifurcation A bifurcation is any abrupt change in the qualitative form of the attractor of a dynamical system or in a system's steady behaviour, when one or more parameters are changed.

Bifurcation diagram A graph that shows the critical points where bifurcation occurs and the possible solutions that exist at each point.

Bullwhip Effect (*see* demand amplification)

Chaos A deterministic, nonlinear dynamic system that can produce random-looking results. A chaotic system must have a fractal dimension and must exhibit sensitive dependence on initial conditions.

Correlation It is the degree to which factors occur in conjunction with each other.

Correlation Dimension It is an estimate of the fractal dimension that (1) measures the probability that two points chose random will be within a certain distance of each other and (2) examines how this probability changes as the distance is increased.

Correlation Integral The probability that two points are within a certain distance from one another; used in the calculation of the correlation dimension.

Critical levels Values of control parameters where the nature of a nonlinear dynamic system changes. The system can bifurcate or it can make the transition from stable to turbulent behaviour.

Cycle A full orbital period.

Demand Amplification It is the result of information distortion about consumer demand moving upstream in the supply chains, which tends to increase the amplitude of the initial change.

Determinism It is a theory that supports that all systems are governed by rules that are predetermined in advance. One of the characteristics of deterministic chaotic systems is that although deterministic they may appear random-looking results.

Dimension of the System The set of variables of the system.

Dimensionality *see* trajectory

Dynamic System It is a set of equations specifying how certain variables change over time.

Entropy It is a measure of disorder or uncertainty in a system.

Equilibrium The stable state of a system.

Feedback System When the output becomes part of the input in the next iteration.

Fourier Transform It decomposes a wave into its component frequencies.

Fractals It is a mathematical object that is self-similar and chaotic. The main characteristics of fractals are (1) they can be generated by relatively simple equations and (2) their shape is consistent at whatever scale or level of detail that they are observed, e.g. looking are a coastline.

Hurst Exponent It is a measure of smoothness of the time series. It provides a measure of whether a trend will persist or mean revert to some historical average. It also indicates the presence of cycles, although these are typically non-periodic.

Initial Condition The original point of a dynamic system.

Linearity The input is equivalent, or linearly related, to the output.

Limit Cycle An attractor (for nonlinear dynamical systems) or a self-sustaining phase loop that represents periodic motion.

Lyapunov Exponent It is a measure of the mean exponential rate of divergence of initially close trajectories. Each dimension has a Lyapunov exponent.

Noise It is randomness.

Orbit (or trajectory) It is the path that a system follows in phase space.

Persistence A tendency of a series to follow trends. If the system has increased in the previous period, the chances are that it will continue to increase in the next period. Persistent time series have a long "memory"; long -term correlation exists between events and future events.

Phase Space Illustrates the possible states of a system by using its dimensions as the variables of the system. Thus every point in the phase space plot represents a potential state of the system.

Range of Data It is the difference between maximum and minimum value of the data.

Sensitivity to Initial Conditions When two identical systems start under nearby identical initial conditions after a certain period of time they will drift apart. This is the result of small changes causing big effects.

Spectrum It is a representation of the underlying time series (quantity) as a function of frequency.

Strange Attractor It is a geometrical shape in phase space that represents the limited region of phase space ultimately occupied by all trajectories of a dynamical system.

Trajectory (or dimensionality) It is simply the progression of the positions that the system fills in the state space from its initial conditions (or, starting point) to and within its attractor.

White Noise Pure randomness.

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